"OPTIMAL CONTROL OF ENERGY USAGE AT THE TASMAN MILL"

A thesis presented for the

degree of DOCTOR OF PHILOSOPHY in ENGINEERING

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CHAPTER 1 INTRODUCTION TO THE THESIS

1.1 PRELIMINARY DISCUSSION

The last decade has seen a rapid growth in the systematic techniques of systems analysis, control and optimisation collectively known as Systems Engineering. Equally rapid has been the development of reliable process control computers, and to a lesser extent, the necessary measurement transducers for process control applications. The growth of technique has created new opportunities for the more economic operation of industrial systems, while the development of reliable hardware has made implementation of this technique feasible.

The primary aim of this study is the development of philosophy and techniques for the optimum control of energy usage within the Tasman mill system. This forms the major part of the thesis, and involves:

(a) analysis, definition and decomposition of the problem

(b) analysis and modelling of the system characteristics

(c) development of a co-ordinated set of algorithms for solution of the problem

(d) synthesis of a forward looking philosophy for the eventual introduction of the modern techniques of optimum control.

The secondary long term aim of the project is the planning of a gradual introduction of systems engineering technique to the firm, aimed at eventual implementation of the energy optimisation techniques developed during the course of the University study. Obviously, this objective cannot be realised completely during the course of a Ph D study, and is dependent on many factors outside the control of the student, however a serious attempt at planning for implementation has been made and is reported on in the thesis.

The subject material of the thesis is therefore firmly oriented towards the pulp and paper industry, and in particular towards the Tasman mill at Kawerau, New Zealand. It is seriously intended that the thesis shall be the foundation on which further work leading to practical implementation will stand. As such, certain sections go beyond matters of principle and consider matters of detail important in practical implementation.

This first chapter serves as an introduction to the thesis and will:

(a) show how the choice of the particular project was arrived at,

(b) give a brief introduction to the papermaking process and the Tasman mill system,

(c) state the major problems encountered during the course of the study and briefly describe the philosophies adopted to solve these problems,

(d) briefly summarise the contents of each chapter within the thesis.

1.2 CHOICE OF PROJECT SPECIFICATION

1.2.1 Type of Study

In view of the commitments of the author to the Tasman Pulp and Paper Company, it was decided at the initiation of the project that the type of study undertaken should be biased towards a major facet of the Company's activities. Major boundaries of the study were to be set by personal interest, applicability to the firm's operations, and the need to satisfy the academic requirements of a Ph D Study. It was also considered desirable that the study discipline allow a choice of project for which an economic return to the Tasman Company seemed likely, and where practical implementation within a time scale of 5 - 10 years was a possibility.

Personal interest, and the production oriented basis of the Company's activities led to the choice of "control" as the broad study discipline. Of the various possibilities within this subject, it was considered advisable to avoid those involving a high degree of specialisation in advanced process technology (1). The particular subject area favoured was "Systems Engineering - Process Computer Control - Operations Research", because:

(i) of the generality of application to the process (1, 2, 3, 4)

(ii) such studies often yield benefits before implementation (5, 6)

(iii) academic requirements can be satisfied while still maintaining generality (7)

(iv) the rapid growth of applications in the field implies that Tasman is likely to take similar steps in the near future (2, 3, 4, 5).

1.2.2. Choice of Project

As pointed out by Lefkowitz (7) academic research fulfills a dual role:

(i) satisfaction of research objectives, i.e. the advancement of the field of interest through the development of new concepts, analytical techniques, methodology, etc.

(ii) supplying the needs of the educational process, essential to both the faculty and the student.

This dual role results in an approach which is not entirely compatible with the approach to an industrial research investigation, in that the latter is more interested in applications of known general methods to a particular detailed case (6, 8, 9). It was considered that the greatest compatibility of interests would be achieved with a project concerned with behaviour of a significant part of the whole system, rather than particular sections of the system, i.e. a project dealing with co-ordination of the mill behaviour and management decision making (10), rather than improving the performance of some particular section of the process with, say, a detailed process computer study (11, 12).

With this background in mind then, the following arguments influenced the choice of project:

(i) Advancement of technique rather than application is desirable.

(ii) The problem must be sufficiently general to ensure breadth of training.

(iii) Problems involving specialist knowledge of the process, or the installation of new equipment should be avoided, owing to the geographic separation of Industry and University.

(iv) Project information should be readily available. Extensive data collection consumes much time and money while yielding little return of immediate academic value.

(v) Projects involving a high degree of employee interaction at any stage should be avoided.

(vi) The project should have a distinct short term objective, and should indicate an economic return.

With the assistance of mill personnel, notably D. Weston (Assistant to the Mill Manager), several projects were investigated within the constraints given above. The study which was considered to satisfy the requirements best, and which was adopted, was "The Optimisation of Energy Usage at the Tasman Mill".

1.2.3. Project Specification

The original project specification as seen by the Tasman Company Limited is reproduced below:

"(i) Investigate the automation of power purchase, generation and distribution, using actual and anticipated power demands -

(a) from the substations resulting from production rates, scheduled shutdowns, paper breaks etc.

(b) from the grinder loads, relating paper machine pulp requirements, groundwood storage and broke storage.

(ii) Using the process control computer required for (i) above, the system should operate so that minimum fuel plus power cost is achieved within the constraints specified.

(iii) The system should continuously calculate from the beginning of the electrical year (1 April) whether the N. Z. Electricity Department maximum demand is optimum (fuel + power cost minimum) and, if it is not optimum, what the new M. D. should be."

Originally, parallel investigations at the firm and the University were envisaged. The former was to be concerned with grinder performance and modelling, and the latter with system-wide co-ordination modelling and optimisation. Unfortunately, the groundwood study did not result in useable information for the University group, as the persons involved, (D. Weston and V. Lawlor) left the Company's employment.

This first specification satisfied the constraints considered in 1.2.2. and has remained largely unchanged. With an annual energy cost of approximately $3 million, an economic return on the project would appear feasible. An additional possible benefit of the particular project is that it ideally can serve as a vehicle for the systematic introduction of modern control techniques to the Tasman Pulp and Paper Company.

The preceeding sections (1.2.1., 1.2.2. and 1.2.3.) have described the investigations into the choice of the most suitable project which were undertaken at the initiation of the study. Firstly, the most suitable type of study, or research area was determined, secondly the requirements as to the choice of a particular project were considered, and thirdly, a specification of the particular project selected was outlined.

The original specification was, therefore, carefully chosen to provide definite benefits to both the Firm and the University in a co-ordinated University/Industry effort, the regrettable loss of the supporting effort at Tasman necessitated a reduction in the detailed quantitative area of the study originally intended.

1.3 AN INTRODUCTION TO THE TASMAN MILL SYSTEM

1.3.1. The Tasman Mill and Departmental Structure

The Tasman Mill System is a complex organisation engaged in the production of newsprint, kraft pulp and sawn timber. Some 1,500 employees work in approximately 20 acres of buildings spread over the 230 acres (an additional 500 employees are involved in logging operations based at Murupara). Operating and skeleton maintenance crews work in 3 shifts as the pulp and paper mills operate continuously, shutting down only once a year for major maintenance purposes. The sawmill only works 2 shifts per day however, and all parts of the mill are shut down from time to time for maintenance and also, in the case of the paper machines, to change component parts such as wires and felts.

The process involves pulping the timber to its constituent fibres, partly by mechanical and partly by chemical means and reforming the fibres into a sheet of paper or pulp. Although conceptionally simple, on a large production basis this process is exceedingly complex, and has been described as "both an art and a science" (2) due to the scarcity of quantitative technological understanding of the phenomena involved. Interesting control problems abound within the process such as optimum recovery boiler control, optimum groundwood mill control, etc. (2,13,14,15). Figure 1.1 shows the site layout for the expanded mill, and Figure 1.2 indicates the product flow throughout the existing mill.

The size and complexity of the system has led to a multi-level hierarchical structure of control and responsibility. This takes the familiar pyramid like "organizational" hierachy form (16) as shown in Figure 1.3. The mill process is divided into a number of operational sections as indicated in Figure 1.2, each section or department encompassing similar activities. In addition there are the mill-wide service departments such as:

(i) Maintenance
(ii) Electrical
(iii) Engineering
(iv) Steam
(v) Commercial

The mill departments make up the lower level shown in Figure 1.3, co-ordinating control being exercised by the upper levels of the hierarchy.

1.3.2. The System Flowchart

Figure 1.2 illustrates the flows between the major operational units of the system. As can be seen in the diagram, the system has been designed with buffer storage between all units, this giving a degree of flexibility in operation.

Figure 1.4 shows the system in greater detail. Major uses of electricity and steam are indicated. Some process aggregation has been carried out in this presentation, however, it is generally of a minor nature (e.g. the causticizing cycle). Some of the control problems involved in the individual "blocks" of Figure 1.4 require a

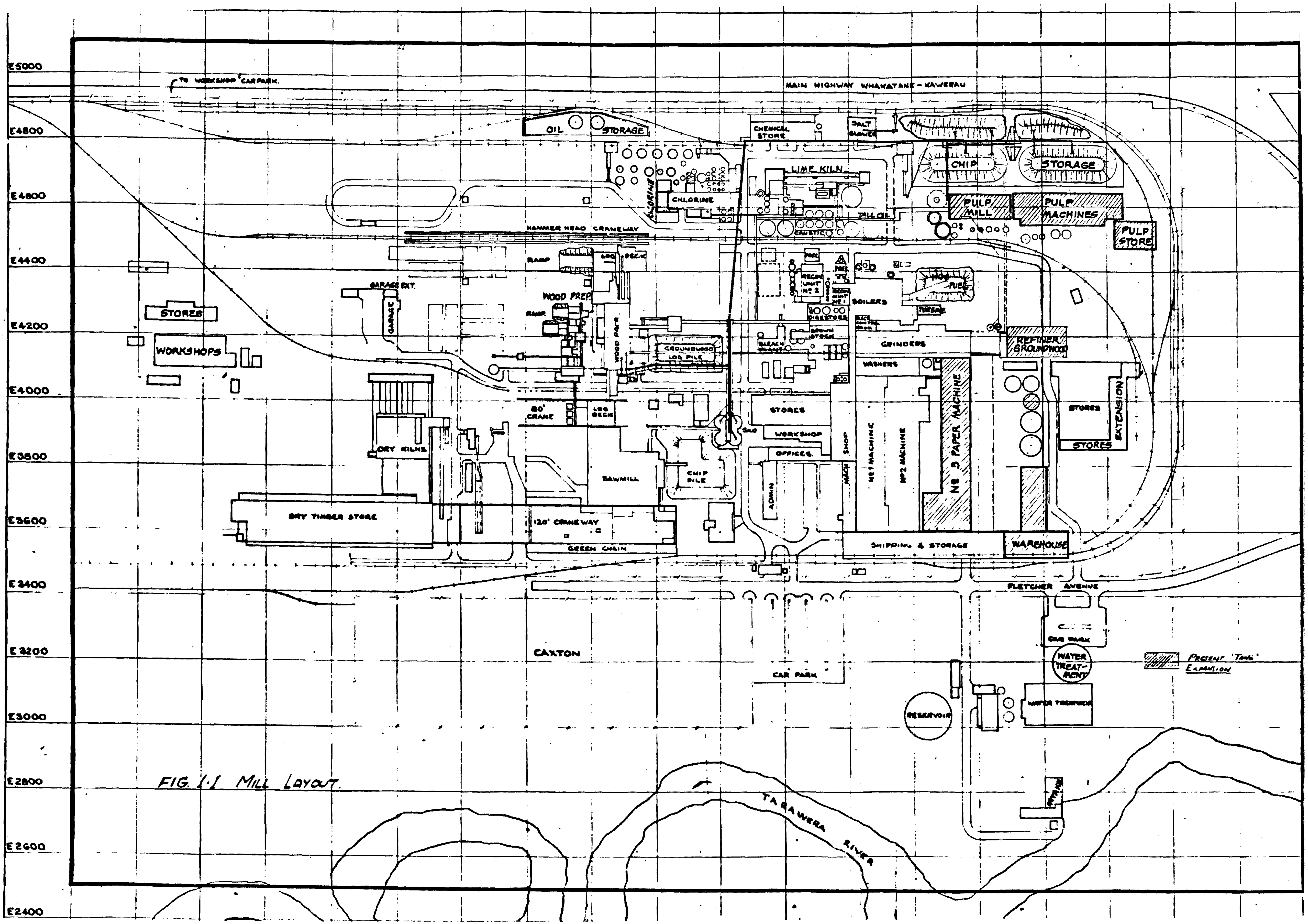

FIG. 1.1 MILL LAYOUT.

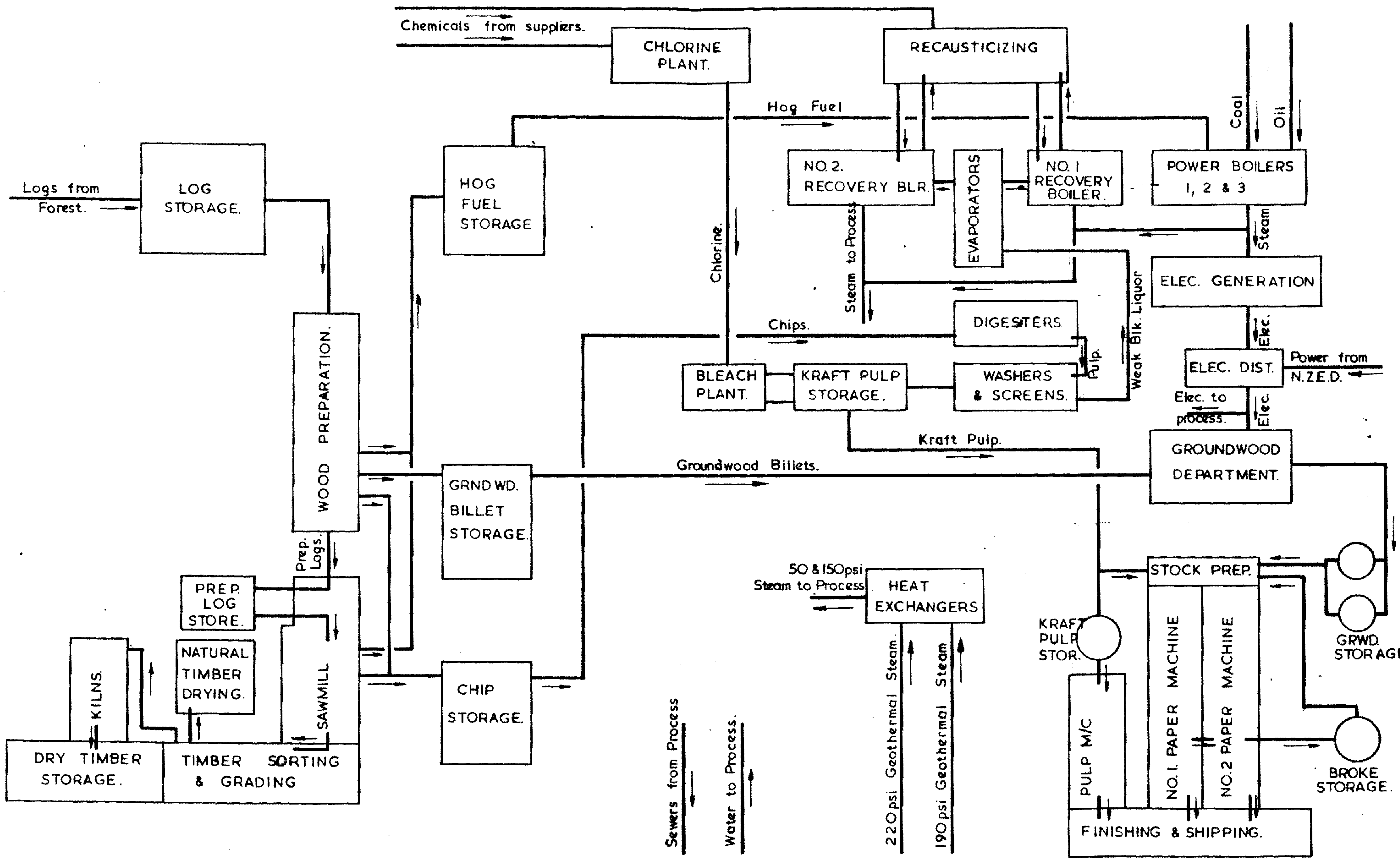

FIG. 1·2 PRODUCT FLOW & DEPARTMENTAL AREAS

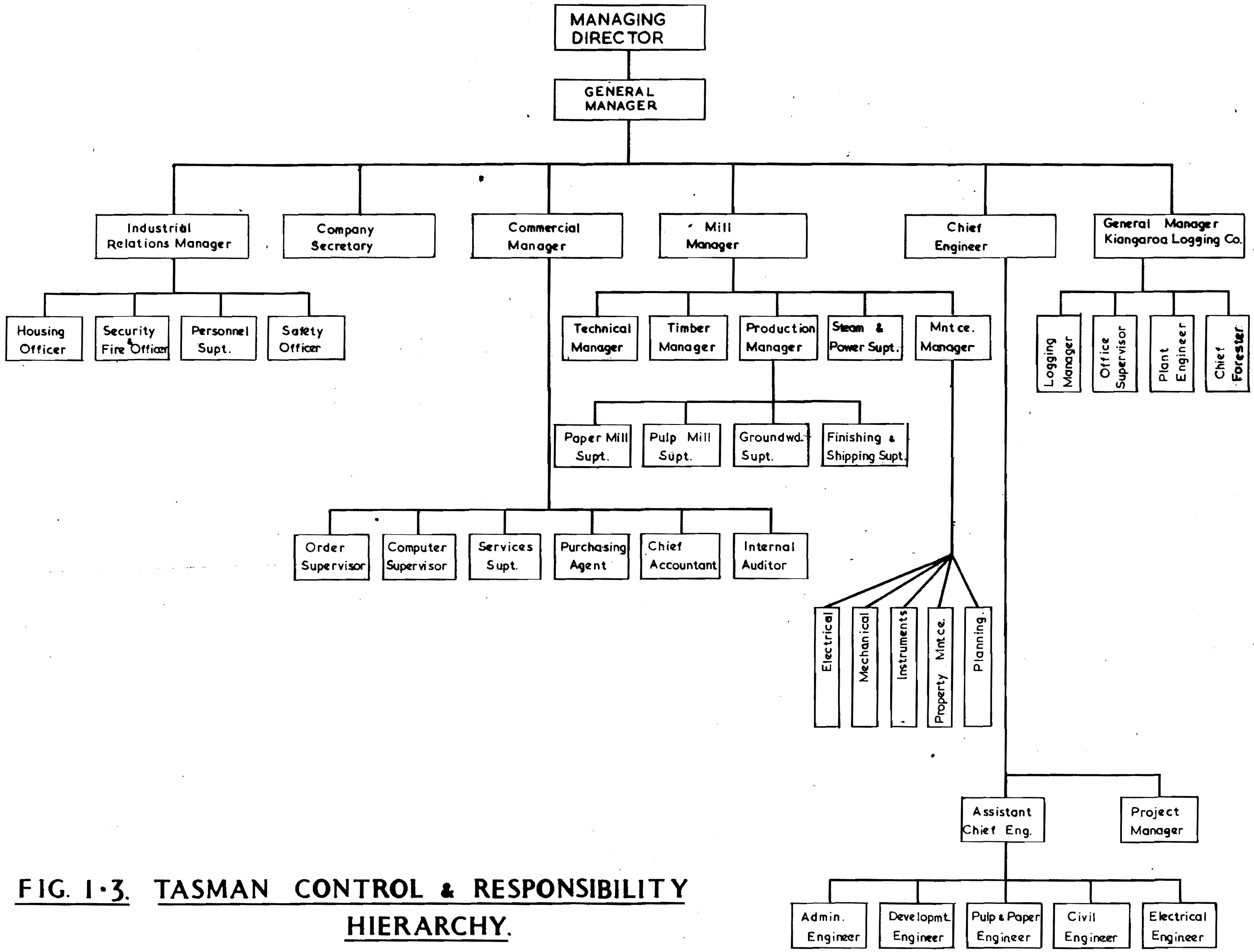

FIG. 1·3. TASMAN CONTROL & RESPONSIBILITY HIERARCHY.

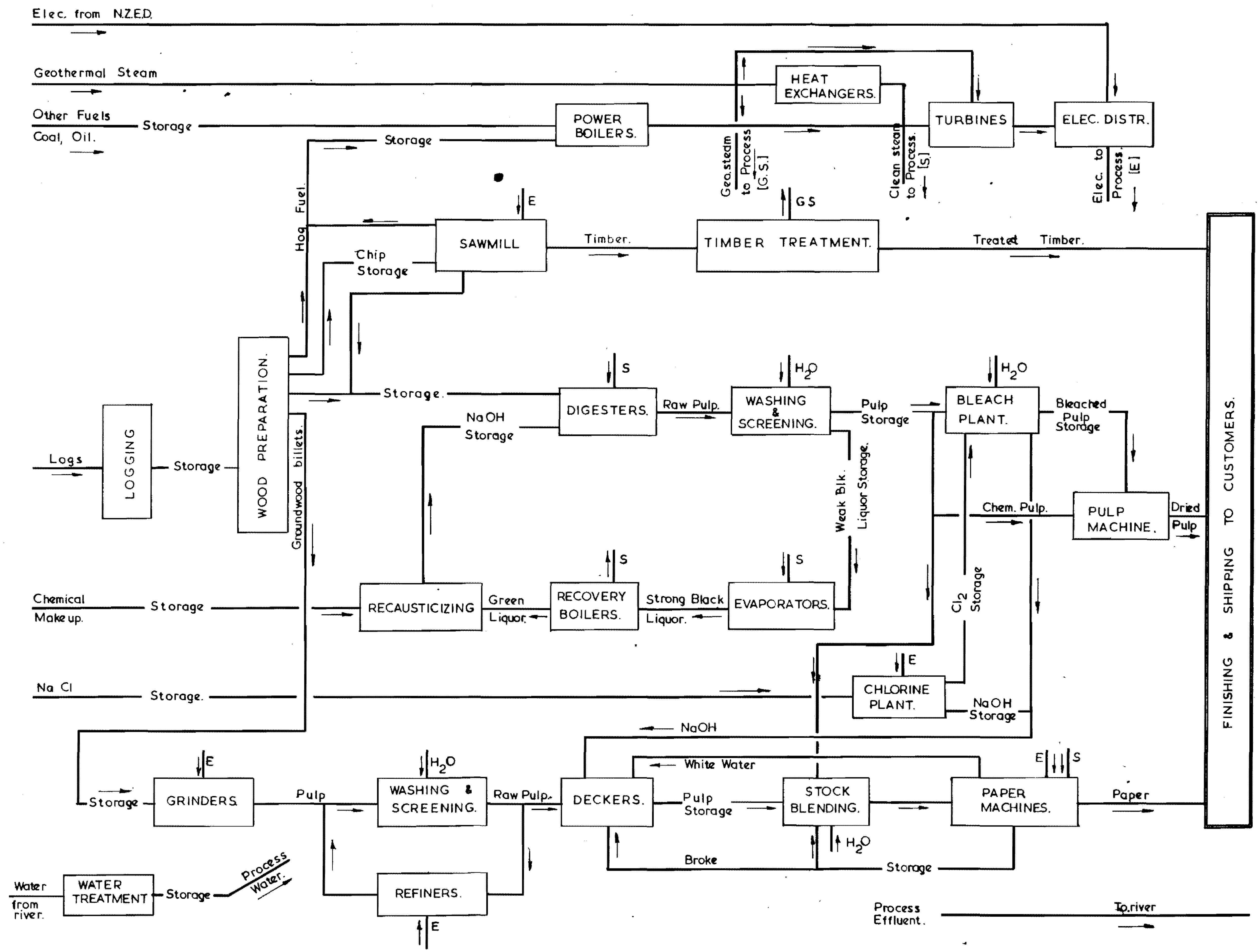

FIG. 1·4 DETAILED REPRESENTATION OF THE TASMAN SYSTEM.

"trade-off" i.e., a compromise solution involving "block" inputs or outputs (e.g. groundwood freeness and quality control involves available electricity supply versus paper machine requirements). The problem of control and co-ordination of each of the blocks so that an overall optimum or best compromise is achieved is self-evident.

1.4 MAJOR PROBLEMS ENCOUNTERED DURING THE STUDY, AND SOLUTION PHILOSOPHIES DEVELOPED

1.4.1. Interfacing the Energy Optimisation Study With Other Aspects of Total Operation

Overall optimum operation of the Tasman mill system includes many subproblems with objectives which are at variance with the objectives of this study. For example, quality or production maximisation. As the energy variables influence all aspects of production activities at all levels, it is necessary that:

(a) the application of optimising technique to the energy control subproblem should not result in less economic total operation

(b) control solutions resulting from future studies can be interfaced with the optimizing control of this study.

This requirement for compatibility of interfacing of energy optimisation with other control subproblems, and with the total overall problem is satisfied in two ways:

(1) Consideration of the economic aspects of the overall problem (i.e. the wider system) results in some restraints to the energy system optimisation, necessary to maintain co-ordinated objectives (see section 2.2.1.).

(2) Decomposition of the wider problem into an hierarchical structure of subproblems from which the decomposed energy optimisation subproblem is isolated (see 2.2.2.), and the use of an aggregation model building policy (see 2.4.1.), allow extension of the problem to include or interface with the other subproblems at any level. This can be achieved by superposition of either active or restraint co-ordination similar to (1) between the levels of the decomposed problem.

The problem of compatibility of the energy optimisation study with other subproblems has been solved by these two methods, both involving consideration of the wider system of which the energy system is a part.

1.4.2. The Problem of Complexity in the Energy Optimisation Operation

Limitations in present optimisation technique preclude a global solution to the problem as specified, owing to:

(i) the breadth of the specification, covering all aspects from management planning to fast acting machine control

(ii) the multivariable structure of the energy control and distribution network.

Decomposition techniques are introduced to fragment the problem into manageable sections while still permitting a near optimal total solution (see 2.3). Sequential decomposition results in:

a. A vertical optimum control structure where each level is determined by speed or frequency of the solutions required.

b. A subordinate horizontal structure determined by separation and co-ordination of the tasks at each level.

The latter structure is imbedded in the time-based vertical hierarchy to give the familiar pyramid-like "organisational hierarchy" (16).

The resulting 'task' structure contains the subproblems of the overall problem, and any required co-ordination between subproblems at the same level. Extension of control to include other related problems, as discussed in 1.4.1. would imply imbedding and co-ordinating the corresponding subproblems at suitable levels to give an extended overall task structure.

Imbedding suitable levels of the model hierarchy in the task hierarchy gives a co-ordinated, extendable, task model structure, i.e., a complete, detailed problem formulation. Application of control and co-ordination techniques at each level results ideally in an optimal solution to the overall problem. Control techniques for each level may be selected from a generalised control hierarchy, but are limited by feasibility and speed of response. Co-ordination techniques may be either interactive, where conflicting objective functions are "balanced", or passive, where restraints are set on the common variables to limit objective function conflict.

Decomposition of the energy optimisation problem into an hierarchical structure of manageable subproblems, is therefore a major technique utilised to overcome the computational limitations of present optimisation methods.

1.4.3. Problems Arising From the Variety of Disturbances to System Operating Conditions

As in any practical system, various disturbances act to modify the state of the system from time-to-time, disrupting the previous conditions for optimum operation. The variety of these disturbances creates a problem in the minimisation of non-optimum operation.

The solution philosophy adopted here is: 1) to analyse and classify the system disturbances explicity with respect to their characteristics, and 2) to utilise this information in the horizontal decomposition of the task structure and in the specification of the design requirements of each subproblem isolated (see 2.3).

This approach to the problem embodies a "divide and rule" concept in grouping the disturbances by characteristics, and specifying separate though related algorithms to deal with each group. More sophisticated algorithms developed later in the thesis (4.3.5.) are capable of dealing with a general class of disturbance.

1.4.4. The Problem of Plant Data Availability and its Limitations

System operational data has been derived principally from plant records. Although relatively plentiful in quantity, this information is not always in a useful form (e.g. circular graphs), and the data sampling frequencies used are often too low to provide a sufficient quality of history of operating conditions. Data inaccuracies also arise through measurement errors and changes in plant characteristics.

The problem here is that these errors greatly reduce the quantitative accuracy of the results of the study. No real solution is possible in the timescale of a Ph D study since the extensive data collection and correlation required would give a poor academic return for the effort involved. However, a typical deterministic weekly cycle and nominal probability distributions have been compiled from the limited data collected. For comparison of the optimising system performance with normal plant operation, a set of plant recordings for Period 9 (35 days), 1968, were compiled (2.4.3.)

For the internal system units, very little information is available on transfer functions applicable. Generally, linear transfer functions have been assumed in modelling the system, this assumption and the co-efficient values used being taken from a Tasman report on simulation studies, and correspondence with various mill personnel.

All system data and modelling assumptions are subject to correction. In the long term it is intended that a study with this objective should be carried out at the plant before any implementation. As mentioned earlier (1.2.3.) this information was originally to have been provided by a team at the firm. The loss of these persons from the Company's employ has created a regrettable reduction in the quantitative aspects of the study.

The problems associated with the lack of quantitative information on the plant characteristics has not been solved in this study, however, the nominal system information utilised has been sufficient to prove the techniques developed.

1.4.5. The Computer Dimensionality Problem of Dynamic Optimisation

Optimal control of systems with dynamic content is notoriously expensive of computational time and storage (17,18). The large time requirement places a definite limit on the speed of application, i.e. defines a level in the time-hierarchical structure below which optimal control cannot be used. This limit varies with:

(i) the dynamic content of the system being optimised,

(ii) the form of the optimisation algorithms used,

(iii) the type of computer involved.

For on-line dynamic optimal control, the dimensionality problem is obviously critical; for off-line advisory programmes the problem is not so serious, although still limiting. Efforts to improve the feasibility of dynamic control in the energy optimisation have assumed a major role in this study, and include:

(i) reducing the model dynamics to a 'best' minimum level consistent with position in the task hierarchy (section 2.4)

(ii) devising new optimising algorithms designed for the particular class of problem. (sections 4.2, 4.3)

Research in this area of the problem is being continued in the Department of Electrical Engineering at the University of Canterbury, particular emphasis being placed on (ii) above, and the use of various computing schemes, especially those with a fast parallel computing capability (e.g. hybrid analogue/digital computers).

This thesis will present a new algorithm termed "Dynostat" which will form the basis of optimum control technology for the specific energy optimisation problem.

1.4.6. Problems Associated with the Introduction of New Technique to Industry

The term is used to emphasise the importance of a planned introduction of substantial new technology such as optimal computer control, to a large organisation. Problems of confidence and competent operation are envisaged if the rate of introduction exceeds the maximum rate of assimulation of the wide range of persons involved, from executive management to shop floor operatives.

To avoid haphazard and sudden changes a planned introduction, typified by a gradual ramp function with time, is proposed. This implementation of the off-line and on-line techniques of the power optimisation is to be spread over several years, detailed checking, feasibility, and cost/benefit studies being carried out. Implementation of optimising schemes would begin at the upper levels of the control hierarchy where high speed is unnecessary, this permitting the system to work in parallel with the human operators, in an advisory capacity. The lower, faster response levels of automatic control could then be systematically introduced.

The gradual planned introduction is seen as the best approach to the problems associated with the introduction of a new technology. Subsequent applications should therefore start off in a favourable confident atmosphere, and be handled on a much shorter timescale.

1.4.7. Summary

The above are the main problems foreseen in solution of the optimum energy control problem, bearing in mind also the wider system implications. Although the techniques proposed to deal with these problems fall well short of perfection, a clear understanding of the problems at the initial stage offer a good foundation from which to work.

1.5 A DIRECTORY TO THE THESIS

The ultimate objective of this project is the development and implementation of a co-ordinated set of optimum control algorithms to optimise the energy usage of the Tasman mill. Complete implementation is outside the scope of this thesis, however a wide range of study, including the techniques of hierarchical analysis, modelling, digital computer algorithm development and programming, and the development of a plan for implementation of the optimising algorithms, has been covered.

The work presented in this thesis can be grouped into eight significant sections:

(1) Analysis of the Wider System and its Interaction with the Energy Optimisation Problem

Section 2.2 considers the compatibility problem discussed in 1.4.1. 2.2.1 considers the wider problem i.e. the overall optimum operation of the Tasman system, from an economic aspect. The obvious requirement that the energy optimisation should not result in less economic overall operation results in some general restraints on the problem objectives. In 2.2.2, the wider problem is decomposed into an hierarchical structure of subproblems from which the components of the energy optimisation problem can be isolated. This approach allows extension of the problem to include or interface with the other subproblems at any level.

(2) Hierarchical Decomposition of the Energy Optimisation Problem and the Specification of Suitable Algorithms.

Section 2.3.1 solves the complexity problem discussed in 1.4.2 by decomposition of the overall energy optimisation problem into a set of co-ordinated sub-problems. Both vertical and horizontal decompositions are employed, resulting in a pyramid like "organisational hierarchy". In 2.3.2. the preliminary requirements of the algorithms to solve these subproblems are established.

(3) Development of Suitable Models of the Tasman System

Section 2.4 is concerned with the development of models of the Tasman system for use in the energy system optimisation. In 2.4.1. process models of the system are developed utilising an aggregation technique. A mathematical formulation and objective function are presented, and a hierarchical model structure, suitable for expansion to include other possible studies is given. In section 2.4.2, the various disturbances to the system are analysed resulting in classification of their major components. Models of the primary disturbances affecting the energy subsystem are also presented. 2.4.3 presents a simple model of a typical month of system operation for comparison of existing practice with the control actions of the optimising algorithms.

(4) Survey and Development of Existing Algorithms for Optimum Control

Chapter 3 is devoted to the modification of existing control algorithms to solve suitable of the subproblems of the overall energy optimisation problem as determined in 2.3. Section 3.2 briefly surveys relevent applications of optimal control algorithms, further references being made where applicable throughout the remainder of the chapter. In 3.3 algorithms are developed from existing technique for the long term problems on the upper layer of the problem hierarchy. In section 3.4, application of existing technique for the intermediate term problems is attempted.

(5) Development of the Dynostat Algorithms for the Intermediate Term Problems

Section 4.2 is concerned with the synthesis of the off-line and on-line Dynostat algorithms to solve the optimum scheduling problem of the intermediate term level of the problem hierarchy. An attempt to utilise existing technique to solve this problem was made in 3.4, however this did not result in a satisfactory solution. Attempts to use dynamic programming methods were frustrated by the computational dimensionality barrier (see 1.4.5), and so the Dynostat technique was evolved as a solution to this difficulty. 4.2.1 describes the evolution of this new technique, resulting in the off-line Dynostat algorithm. 4.2.2 presents the further development of the technique to give an on-line capability. In 4.2.3, a heuristic algorithm to solve the optimum scheduling problem is proposed.

(6) Development of Sensitivity Analysis Algorithms for the Intermediate Term Problems

Section 4.3 presents the evolution of techniques to analyse the sensitivity of the optimum schedules to the various disturbances which affect the system. At each level of development increasingly sophisticated methods of correcting for the disturbances are incorporated in the new algorithms. In 4.3.5, a powerful new composite optimisation algorithm incorporating sensitivity determination and restraints is presented.

(7) A Plan for the Implementation of the Energy Optimisation Techniques

The work presented in Chapter 5 represents an attempt to overcome the difficulties of introducing new techniques to an industrial environment as described in 1.4.6. Section 5.2 is concerned with the development of a philosophy of introduction, while 5.3 presents a plan for the introduction of the energy optimisation techniques and algorithms developed in this thesis.

(8) Summary and Documentation of the Thesis

Chapter 6 concludes the thesis with summaries of

(i) the academic results of the thesis,

(ii) the effects of the project within the industry,

(iii) project documentation in the form of reports and published material,

(iv) areas of the study where future development would be expected.

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CHAPTER 2 SYNTHESIS OF A RESTRAINED HIERARCHICAL STRUCTURE OF SUBPROBLEMS FROM CONSIDERATION OF THE WIDER SYSTEM, AND DEVELOPMENT OF SUITABLE SYSTEM MODELS

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CHAPTER 2 SYNTHESIS OF A RESTRAINED HIERARCHICAL STRUCTURE OF SUBPROBLEMS FROM CONSIDERATION OF THE WIDER SYSTEM, AND DEVELOPMENT OF SUITABLE SYSTEM MODELS

2.1 INTRODUCTION

The system with which this study is concerned is complex, and operates on a large scale. A suitable problem formulation when attempting control of such large scale systems is of extreme importance - it has been claimed that a properly formulated problem is half solved (1).

The objectives of the work reported in this chapter are threefold:

1) To ensure that the objectives of the energy system optimisation are comparable with the total operation of the firm as a whole, and can be coordinated with, or expanded to include, the other component operational subproblems of total operation as required. (The former is approached by consideration of the overall system from an economic viewpoint, the latter by decomposition and hierarchical structuring of the decision making in mill operation).

2) Decomposition of the overall energy optimisation problem into a hierarchical structure of related subproblems of manageable size, and a preliminary specification of required solution algorithms. (The broad decision making structure of (1) above permits the relevant problems to be readily isolated; further decomposition yields the coördinated subproblems and gives initial solution algorithm specifications).

3) Derivation of suitable models of the process, of the disturbances to which the system is subject, and of typical present operation for comparison purposes.

2.2 CONSIDERATION OF THE WIDER SYSTEM

The term "wider system" is defined by Jenkins (2) as that larger system of which the system to be controlled is a part. Although the wider system concept can be generalised to a national or even international level, for the purposes of this study the wider system is taken as covering all aspects of mill operations. Variables outside this sphere will influence the firm's behaviour, but are considered relatively uncontrollable (3, 4, 5).

As pointed out by Jenkins, consideration of the wider system and its objectives:

(i) clarifies the role and defines the boundaries of the system to be controlled

(ii) resolves the conflicting objectives of interlocking or competitive systems at the same level of the plant hierarchy.

2.2.1 General Restraints on the Energy System Optimisation from Consideration of the Economic Aspects of the Wider System

In this section the economic objectives of mill operation are considered in a macroscopic sense. Consideration of the energy optimisation within the framework of the wider system operation leads to some general restraints and observations necessary to maintain coordinated objectives.

The basic objective of the wider system (i.e. the firm) is to maximise the return, r, on investment (shareholders equity), C, over N years, where N is the planning horizon. This objective is formulated here as:

$$\text{Max } (r) = \text{Max } \frac{\text{Nett Total Profit}}{C}$$

Let S_n = value of sales in year n

K_n = value of borrowed capital in year n

k_n = interest rate on K_n in year n

L_n = total labour employed in year n

w_n = wage rate in year n

E_n = energy used in year n

e_n = energy cost per unit in year n

ΔC_n = earnings channelled into capital in year n

M_n = maintenance cost (less labour) in year n

D_n = depreciation allowance year n

T_n = taxes in year n

O_n = overhead cost in year n

Then the objective of the firm may be expressed as:

$$\text{Max } r = \text{Max} \sum_{n=1}^{N} r_n$$

$$= \text{Max} \sum_{n-1}^{N} \left[\frac{\{S_n - R_n - k_nK_n - w_nL_n - e_nE_n - M_n - D_n - O_n\} + D_n - T_n - \Delta C_n}{C + \sum_{i=1}^{n-1} C_i} \right]$$

$$= \text{Max} \sum_{n=1}^{N} \left[\frac{\{b_nP_n - R_n - k_nK_n - w_nL_n - e_nE_n - M_n - D_n - O_n\} + D_n - T_n - \Delta C_n}{C_n} \right]$$

$$= \text{Max} \sum_{n=1}^{N} \left[\frac{\{b_nf(C_n + K_n, L_n) - R_n - k_nK_n - w_nL_n - e_nE_n - M_n - D_n - O_n\} + D_n - T_n - \Delta C_n}{C_n} \right]$$

Where: R_n = cost of raw materials in year n

P_n = saleable production in year n

b_n = product price in year n

C_n = total invested capital in year n

P_n = $f(C_n + K_n, L_n)$ = production function in year n

T_n = function of $\{\ldots\ldots\}$

This maximisation is carried out by two groups, the shareholders (as represented by the Board of Directors), and management. In general the shareholders make the long term dynamic financial decisions on the basis of estimated prices and markets, while management is responsible for optimum operations within the financial constraints. The latter is of principal interest here, the former being more in the realm of applied economic theory (3, 4, 5).

The management task is to utilise the capital works appropriation (and to some extent, the maintenance and operations appropriations) to increase : 1) the saleable production, 2) the quality of the product (within defined limits), or 3) the efficiency of the production process (through reduction in % system input quantity costs, i.e. labour, raw materials, energy). Expenditure of the appropriation is governed by the estimated return on capital for all expenditure possibilities.

The energy system optimisation falls into category (3) above, and is consistent with the aims of the wider system, provided that production and quality targets are not jeopardised.

Further consideration of the concept of the wider system with regard to the above discussion, and to the mill system as represented in Figure 2.1, leads to the following requirements for, and observations on, overall optimal control:

(i) The energy optimisation must not prejudice the supply of energy or other inputs of suitable quality (e.g. intermediate products) to the final production units in the process (i.e. paper machines and pulp dryers). To do so would result in less economic overall operation as these units produce the only direct income to the process, and are worked at continuous maximum possible production. This restraint does not apply to the sawmill to the same extent as it does not generally work to a maximum capacity, and thus lost production can be made up.

(ii) The energy optimisation and control system should include a means of analysis of the return on capital for the various expenditure possibilities within the energy system. This planning evaluation function would assist objective decision making in the management capital allocation task.

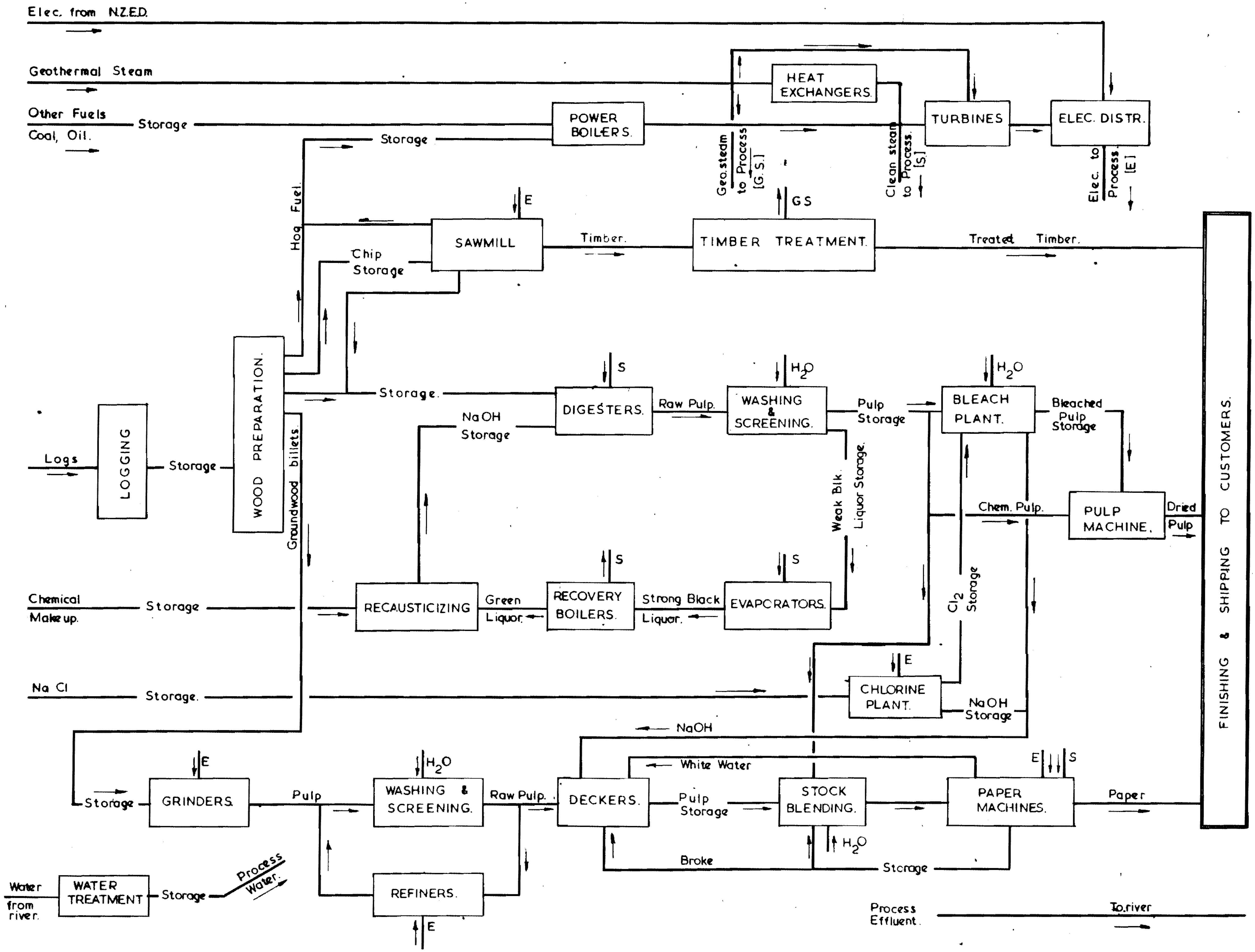


FIG. 2·1 DETAILED REPRESENTATION OF THE TASMAN SYSTEM.

(iii) Flexibility of the optimising control systems is necessary as circumstances both inside and outside the system are subject to constant change, e.g. coal and oil fuel prices and availabilities vary, electricity price structures are subject to change (6), system production capabilities vary, and the technology of the process is improving.

(iv) The presence of buffer storage at practically all stages in the process allows the excess production capability of intermediary units in the production process to be utilised to reduce peak energy demands. This reduces the requirement for standby generation capacity, or permits reduction in the maximum demand on electricity from the New Zealand Electricity Department (NZED). Additional controls in the energy optimisation therefore, are the production rates with time of the intermediary process units.

(v) Process optimisation to minimise energy usage and maximise product quality within each unit of the plant with respect to production requirements is an additional possible control function. This function is not envisaged within the terms of the present study owing to limitations of data and specific knowledge of the topics. It has, however, been specifically considered with respect to co-ordination with the present study to allow later development to proceed within the existing framework.

(vi) Optimal maintenance scheduling would result in improved system operation in ensuring that best use is made of available downtime with respect to production, quality, energy, and the availability of maintenance labour and equipment. Within this study, optimal maintenance will only be considered in its interaction with the energy control task. This is necessary to ensure co-ordination of later development when the detailed data and plant experience is acquired.

The above comments arise from consideration of the economic aspects of the operation of the wider system. They include prerequisites of the energy system optimisation to ensure that this does not yield less economic overall operation, and some more general comments on the energy system optimisation and other closely related sub-problems encompassed within the wider system.

2.2.2 Hierarchical Decomposition of the Wider System Into a Structure of Related Sub-problems

The objectives of the wider system were considered from a macroscopic or management viewpoint in 2.2.1 above. Some general observations were made on the interaction of the objectives of the energy system optimisation and the optimum operation of the wider system.

The aim of this section is to identify the major operational problems of the wider system in hierarchical form and to utilise this structure to construct a decision making hierarchy for the wider system. The sub-structure including the energy optimisation task may then be isolated, and its interactions with the wider system can be clarified and resolved.

While detailed solutions to all the sub-problems determined are not expected in the course of this study, the hierarchical analysis of this section nevertheless provides a framework to co-ordinate further research into control of the Tasman system.

Many applications and philosophies, (e.g. the ARCH philosophy of 1959 (7), predate the development of a hierarchical theory; these drawing on particular configurations in various industries, and the experience and ingenuity of design engineers. Some examples where hierarchical approaches to integrated plant control have been developed are:

1. Iron and steel (7, 8, 9, 10, 11, 12, 13)
2. Refineries (14, 15, 16, 17, 18, 19)
3. Chemical Plants (7, 16, 20, 21, 22)
4. Electrical Systems (7, 23, 24)

A short summary of some applications is given in (1). A computer language for hierarchical control is developed in (25).

Although some elements of hierarchical theory have been known for some time (e.g. the work of Kron in 1939), it is only in recent times that a unified theory has begun to evolve. At this point in time, however, the work is not comprehensively formalised, serving mainly as an inspiration for, and a guide to, application. An account of the historical development of hierarchical concepts and theoretical techniques is given by Mesarovic et al (26). Other major publications in the field, principally with respect to specific techniques, include those of Mesarovic, Findeisen, Pearson, Pliskin and Lefkowitz (1, 14, 15, 17, 18, 27, 28, 29, 30, 31, 32).

The approach taken to this particular application makes use of the theoretical studies mentioned above, and the peculiarities of both the problem, and the system to be controlled. Initially a vertical decomposition is made, resulting in a layer structure. This is followed by a primary horizontal decomposition of the problems on each layer. A control structure is overlaid on each level (33), and finally, the introduction of the stratified model of 2.4.1.5 provides the basis for a secondary horizontal decomposition.

A summary of the steps in this procedure is presented in sections 2.2.2.1 to 2.2.2.4.

2.2.2.1 Vertical Decomposition

This decomposition is based on the frequency of solutions required, i.e. the time horizons of interest in operation of the mill complex.

Figure 2.2 shows the resultant layer hierarchy (1, 16): the result of substituting a structure of sub-goals, each with its own decision making structure, for a complex monolithic goal.

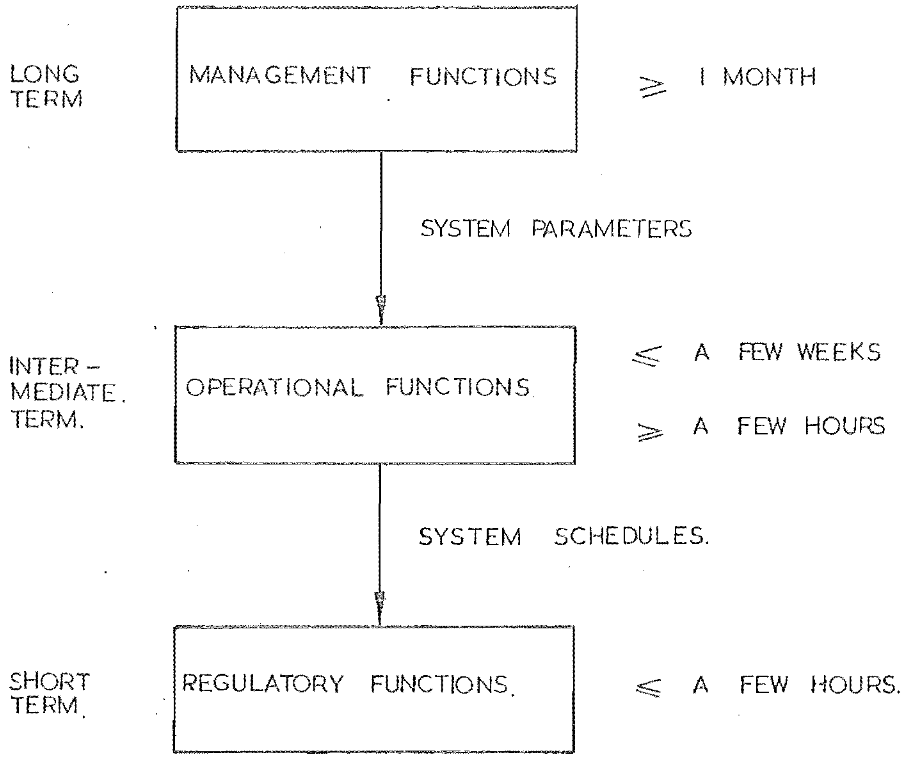


FIG. 2·2 VERTICALLY DECOMPOSED PROBLEM STRUCTURE.

As can be seen in the diagram, the Tasman mill system has three basic operational time horizons:

(i) Long Term: for long term planning and for the optimisation of certain plant parameters which are negotiated or reviewed on an annual basis, e.g. the maximum demand (M.D.) restraint on electric power purchased from the State. Speed of decision making is not generally a stringent problem.

(ii) Intermediate Term: executive engineering and operative functions such as production and maintenance scheduling.

(iii) Short Term: operative system control, viz., meeting production targets, and system constraint and restraint satisfaction (e.g. energy balances etc.)

2.2.2.2 Primary Horizontal Decomposition and Secondary Vertical Decomposition

Three basic layers have been established by the primary vertical structuring. The decomposition of this section is based on separation and co-ordination of the various sub-problems of each layer.

The resultant structure is shown in Figure 2.3. At each layer of the structure, relevant information on past and present system behaviour can be obtained using a data acquisition, storage and retrieval system. Similarly, a forecasting unit at each level utilises suitable parts of this information to produce forecasts of system performance over the time horizons of interest.

On the long term layer of the hierarchy, a secondary vertical decomposition into long term planning and shorter term planning is possible. The former involves analysis of factors external to the mill system (e.g. market growth, world productions and prices etc.) and optimum decisions on the basis of these analyses. A horizontal decomposition into analysis and decision making can thus be seen. Short term planning involves determination of optimal system parameters with respect to expected sales and production determined by long term considerations. A similar horizontal decomposition applies.

On the intermediate and short term layers the overall task decomposes into two related sub-tasks - optimum scheduling or plant control, and optimum maintenance. The solutions to each of these problems require co-ordination to achieve overall optimality.

A horizontal decomposition of the decision task at each level can be derived as a function of the information available. Deterministic data implies decision making under certainty; probabilistic data implies decision making under either risk or uncertainty, depending on the quality of the data. At all levels of the hierarchy in this case, both deterministic and probabilistic information

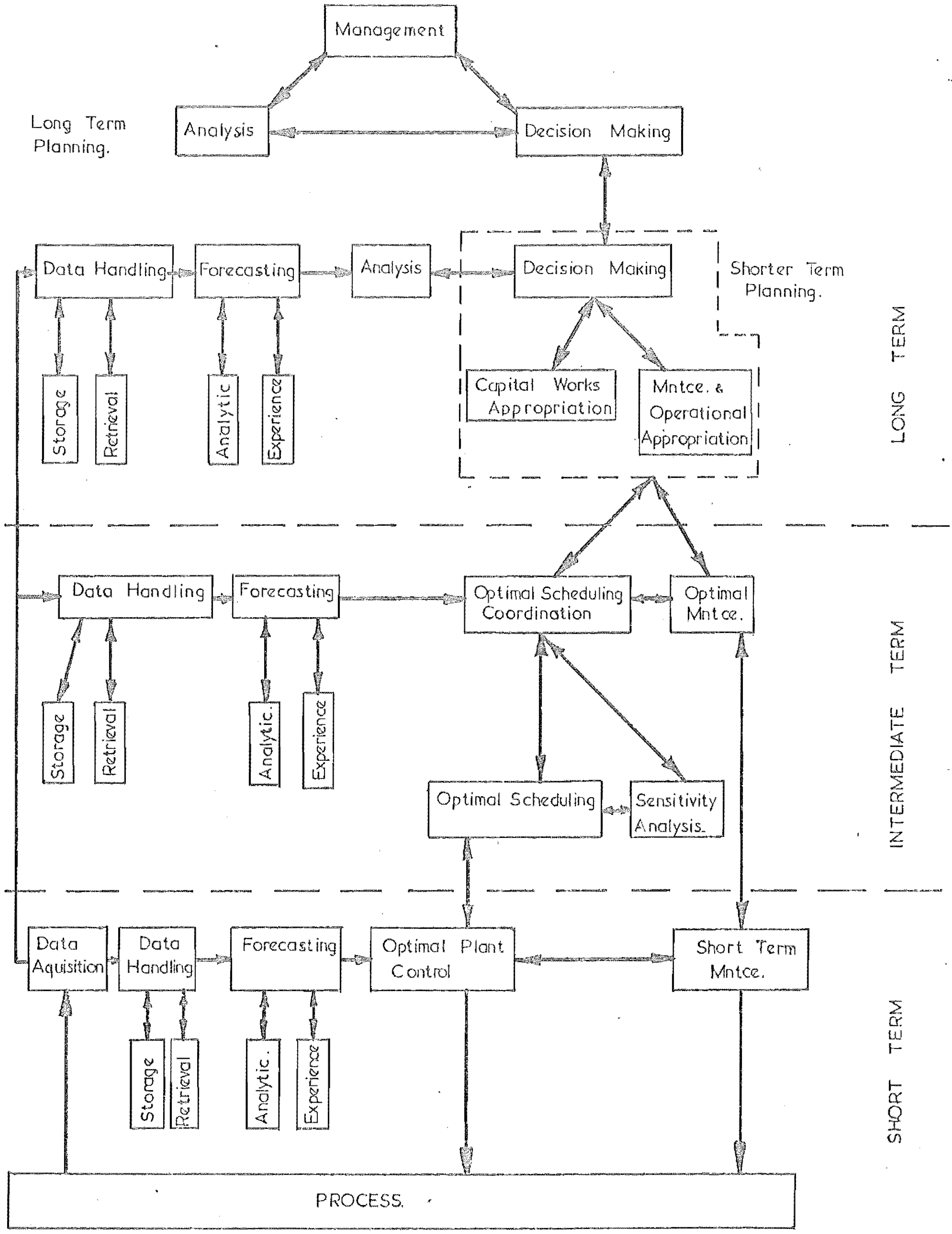


FIG. 2·3 DECOMPOSED PROBLEM STRUCTURE

will be available. Thus the nature of the problems at each layer of the structure can be regarded as decision making under mixed conditions of certainty, risk, and uncertainty (34). To ease the study and solution of the scheduling problem at the intermediate level, a semi-artificial division into deterministic and probabilistic problems can be made. This decomposition can be regarded as giving the associated problems of optimisation, and sensitivity analysis.

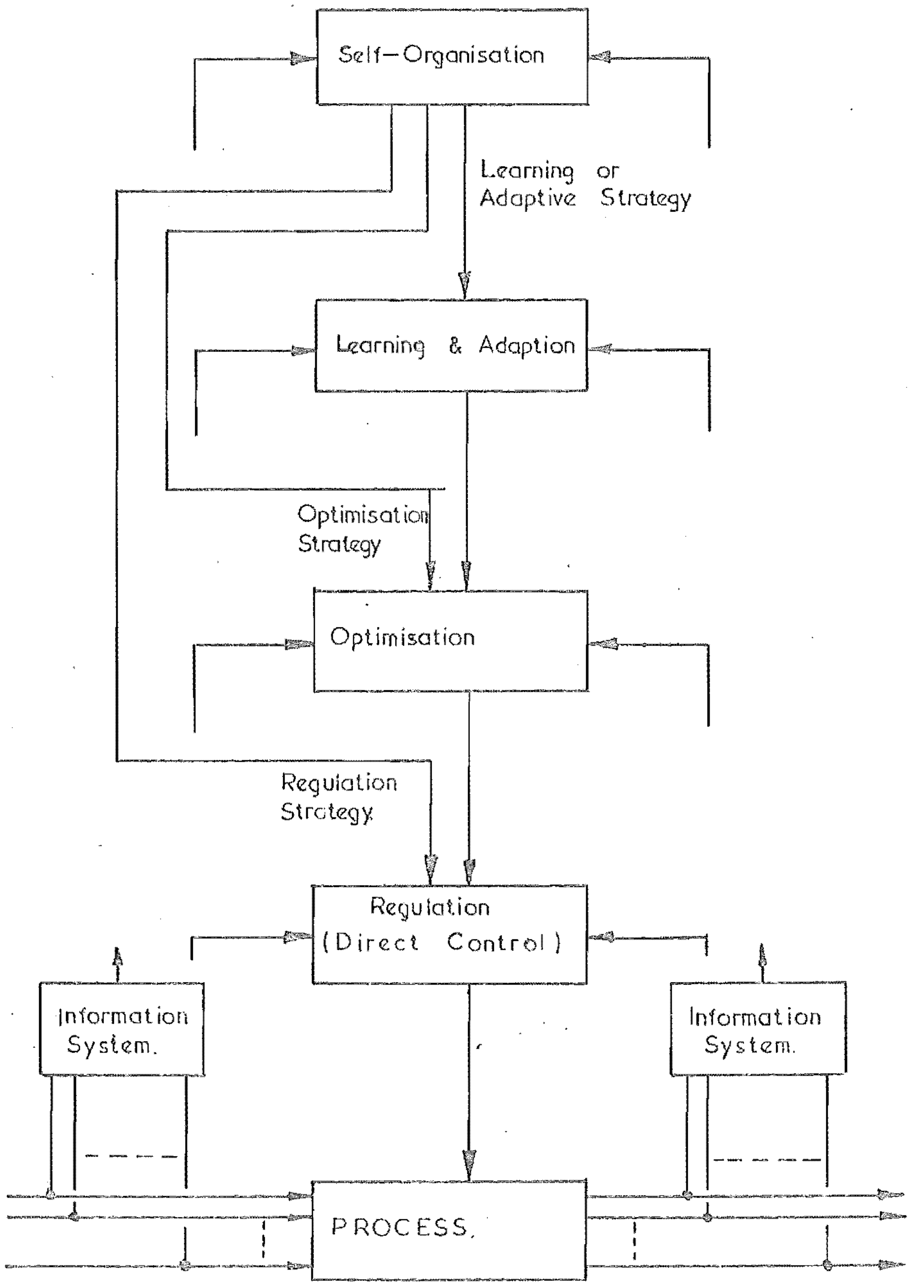


FIG. 2.4 FUNCTIONAL LAYER DECISION HIERARCHY.

2.2.2.3 Control Structure

The nature of the control structure on each level of the problem hierarchy can be determined by consideration of the general "functional layer decision hierarchy" of Figure 2.4 as "overlaid" on each echelon, rejecting those layers which are inappropriate or infeasible. The formulation of this "functional layer decision hierarchy" is extensively discussed in (1, 28).

The resulting control structure is shown in Figure 2.5

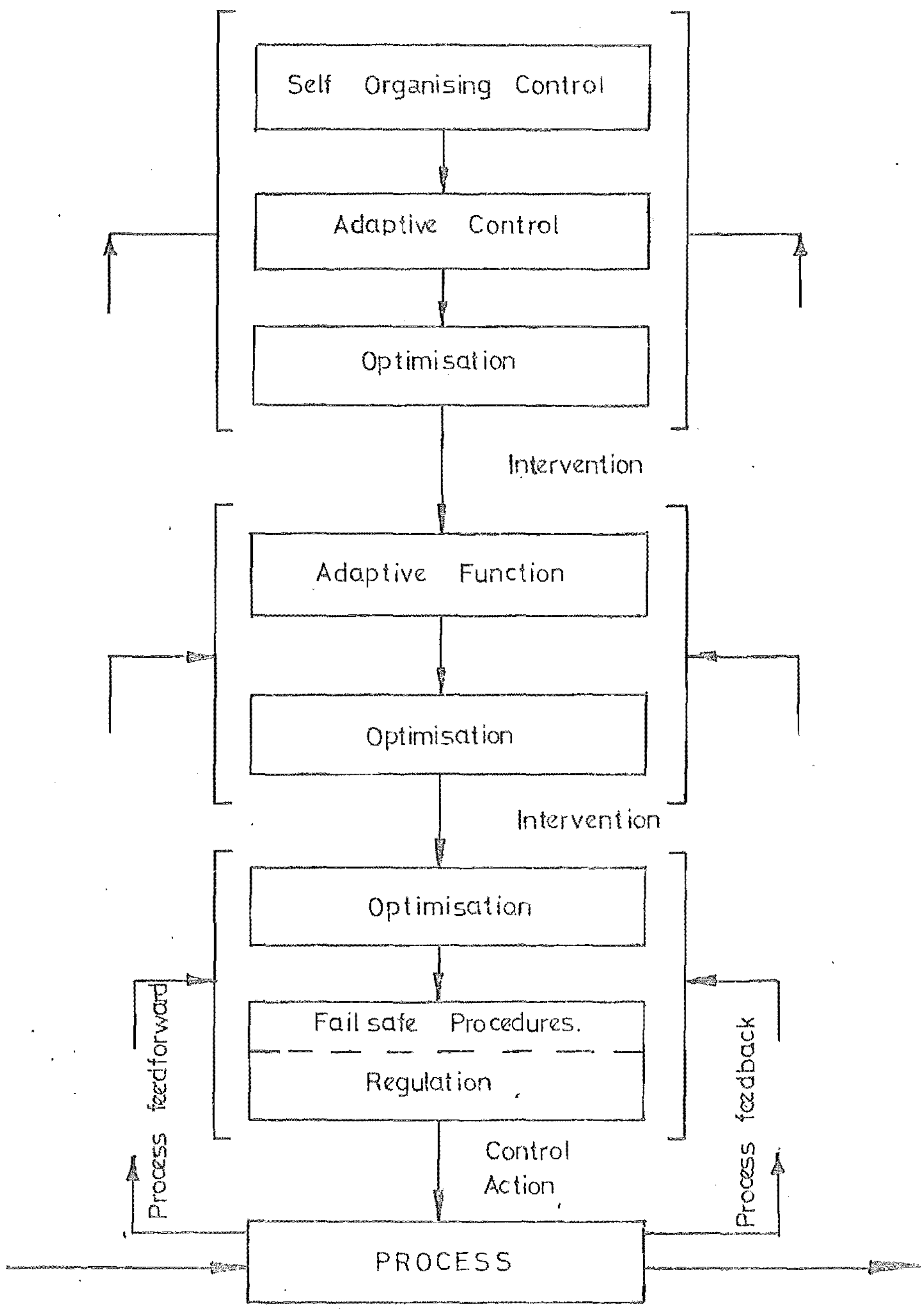


FIG. 2.5 CONTROL FUNCTION HIERARCHY

On the long term level the low speed of response required, complexity, poor problem definition, and the greater degree of uncertainty require that decision making at this level contain self-organising, adaptive, and optimising functions.

At the intermediate level, problems can be more readily formalised quantitatively, thus self-organising control is inappropriate. System parameters and configurations can change however, thus some adaptive function is required, although this can initially be performed by human intervention. Occurrence of unexpected disturbances to the system require that the previously optimum schedules with time be rapidly updated - optimisation must therefore include an on-line facility.

A major requirement at the short term level is speed of response. Optimisation at this level will be on-line to cope with system disturbances; and relatively unsophisticated, to give the desired speed. This level of control is closest to the process, and therefore will include regulation functions, with corresponding actuators and sensors. In addition, failsafe procedures may be required to guard against failure of higher level units.

2.2.2.4 Secondary Horizontal Decomposition

The basic subproblems involved in control of the Tasman mill system have been presented in hierarchical form, along with a suitable control structure for their solution. A further horizontal decomposition of the problem structure may be made, based on the stratified system model of 2.4.1.5. This model, as will be discussed, is the minimum viable model for the general problem of control of the Tasman system; it may however, be "expanded" without drastic re-organisation, for more detailed control of this, or other related problems.

Imbedding the hierarchical model of Figure 2.18 results in the fully decomposed problem hierarchy of Figure 2.6.

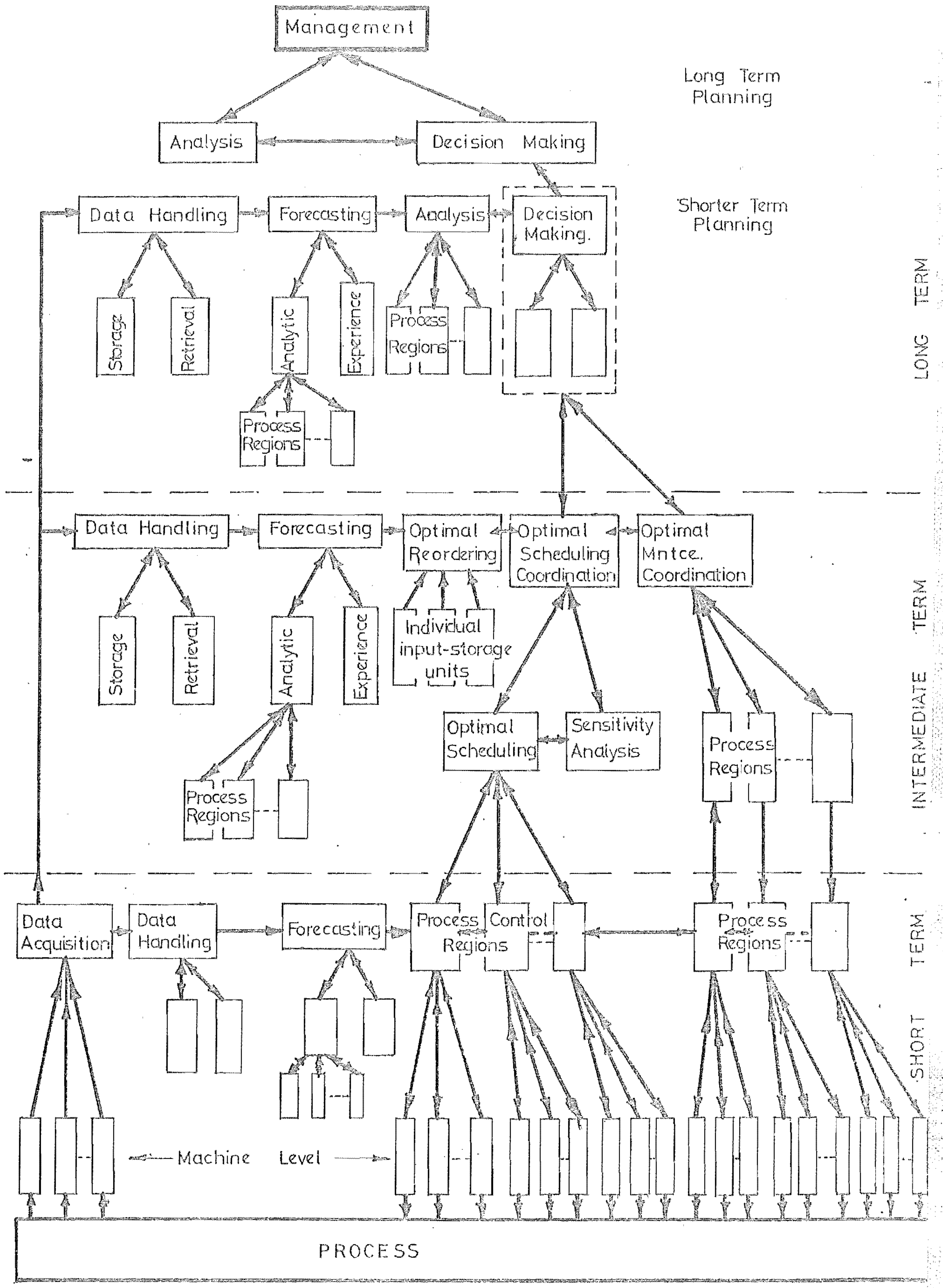


FIG 2·6 TOTAL PROBLEM STRUCTURE

Horizontal decomposition of the process control problem, i.e. the short term level, is evident in the diagram. Co-ordination of individual process areas is carried out as necessary by the overall internal scheduling unit. This could most readily be achieved by a primal technique (27).

More generally, any unit (at any level in the structure) which utilises the model in the course of computation can be subjected to a horizontal decomposition and subsequent co-ordination based on the structure of the model (1, 26, 27). As these techniques were not utilised to a great extent, further discussion is limited, however, the additional units where such methods could be used are as follows:

(i) Long Term: forecasting and analysis functions.

(ii) Intermediate Term: forecasting and optimal maintenance.

(iii) Short Term: data acquisition, forecasting and short term maintenance.

2.2.2.5 A Summary of the Hierarchical Decomposition of the Wider System

Sections 2.2.2.1 to 2.2.2.4 have presented a step by step decomposition of the problem of total operation into an hierarchical structure of related subproblems. A generalised control structure for optimum control and regulation has also been presented. The final hierarchy of Figure 2.6 may be considered as a decision making structure by which the entire process may be controlled, while Figure 2.5 shows the manner in which the decisions should be made, or the control exercised.

This hierarchical structuring of the wider system serves three functions:

(i) it aids understanding of the system, and the behaviour of the system, as a whole, by breaking down the total operational problem into manageable related subproblems.

(ii) it forms a basis for the separation of the energy optimisation substructure, and permits ready identification of the interactions between the energy optimisation substructure, and the wider system structure.

(iii) it serves as a framework for the co-ordination of future research into optimum control of the Tasman mill system.

2.3 SYNTHESIS OF AN HIERARCHICAL STRUCTURE OF RESTRAINED SUBPROBLEMS FOR THE ENERGY OPTIMISATION STUDY

2.3.1 Isolation of the Energy Optimisation Subproblem Hierarchy from the Subproblem Hierarchy for the Wider System

A hierarchy for the control of all aspects of planning and process operation has been developed for the Tasman system as shown in Figure 2.6. This meets the requirement for a complete, overall, "expandable" problem formulation - it is expected that future research will be based on this structure so as to ensure that overall control efficiency is increased.

Units of the control hierarchy concerned with the energy optimisation problem of this study may readily be separated from this overall hierarchy, giving an energy optimisation "substructure". Certain elements of this structure, although related to energy optimisation studies and thus included in the energy control sub-hierarchy cannot be considered in detail, principally due to limitations of time and available data. These units will be considered individually at each level.

Separation of the energy control substructure from the structure of Figure 2.6 can be performed by consideration of each echelon of the overall organisational hierarchy:

(i) Long Term

Energy optimisation is not considered implicitly in the "long term planning" aspects of this level, concern here being more involved with interaction with the "outside world".

Shorter term planning however, is concerned with optimum system configurations within the restraints of available capital. The total process on this level may be considered as:

1) Given previous system performance (data handling), determine forecasts for the coming period.
2) (analysis); determine the marginal return of capital and effects on process sensitivity to system disturbances, for each subsystem of the horizontally decomposed system (e.g. groundwood pulp section, turbo generation section etc.)
3) (decision making) determine the capital expenditure for each subsystem, given the analysis information.

The energy subsystem is involved in this process directly and indirectly. Direct involvement arises from consideration of the energy subsystem as a capital allocation alternative. This requires that the subsystem be analysed to determine the marginal return of capital and process sensitivity, as above, for the various expenditure possibilities available. The indirect involvement arises from the interaction of the energy network with all subsystems of the mill: an increase in the production of some subsystem involves an increase in the supply of energy required. This generally will require expenditure of capital within the energy subsystem, thus analysis is necessary to determine an optimal solution to the increased supply situation. The analysis procedures in both cases are similar, differences involve values of the energy subsystem constraints and restraints.

Data handling and forecasting functions are relevant to the above analysis but are not considered in detail. These functions are carried out manually at present; automation is outside the scope of the project. The assumption is made that required information will be available.

Given the results of the various analyses, decision making is largely a management function, and thus not considered in this study. It is expected that analytic techniques may assist in the decision making process at a later date.

(ii) Intermediate Term

As discussed in 2.2.2.4 energy optimisation at this level involves the energy supply and distribution, and production scheduling problem. The energy control sub-structure consequently contains this problem.

Data handling, forecasting and maintenance scheduling are carried out manually at the present time. Again, the use of analytic techniques is regarded as a subject for future research, data and time limitations preventing investigation at this stage. It is assumed that information regarding the interaction of these units with the optimal scheduling units is available.

(iii) Short Term

Data organisation, data handling, forecasting and maintenance units are regarded in a manner similar to above.

Process control and optimisation units have a direct relationship with the optimal scheduling unit of the intermediate level. Direct process control is not proposed at this stage, consequently the process areas can be aggregated into mill base loads as in 2.4.1.2. Extension of the control to specific process units can readily be achieved by expansion of this level of the model (2.4.1.5).

From these considerations an hierarchical structure for the overall energy optimisation and control problem can be drawn up. This is shown in Figure 2.7.

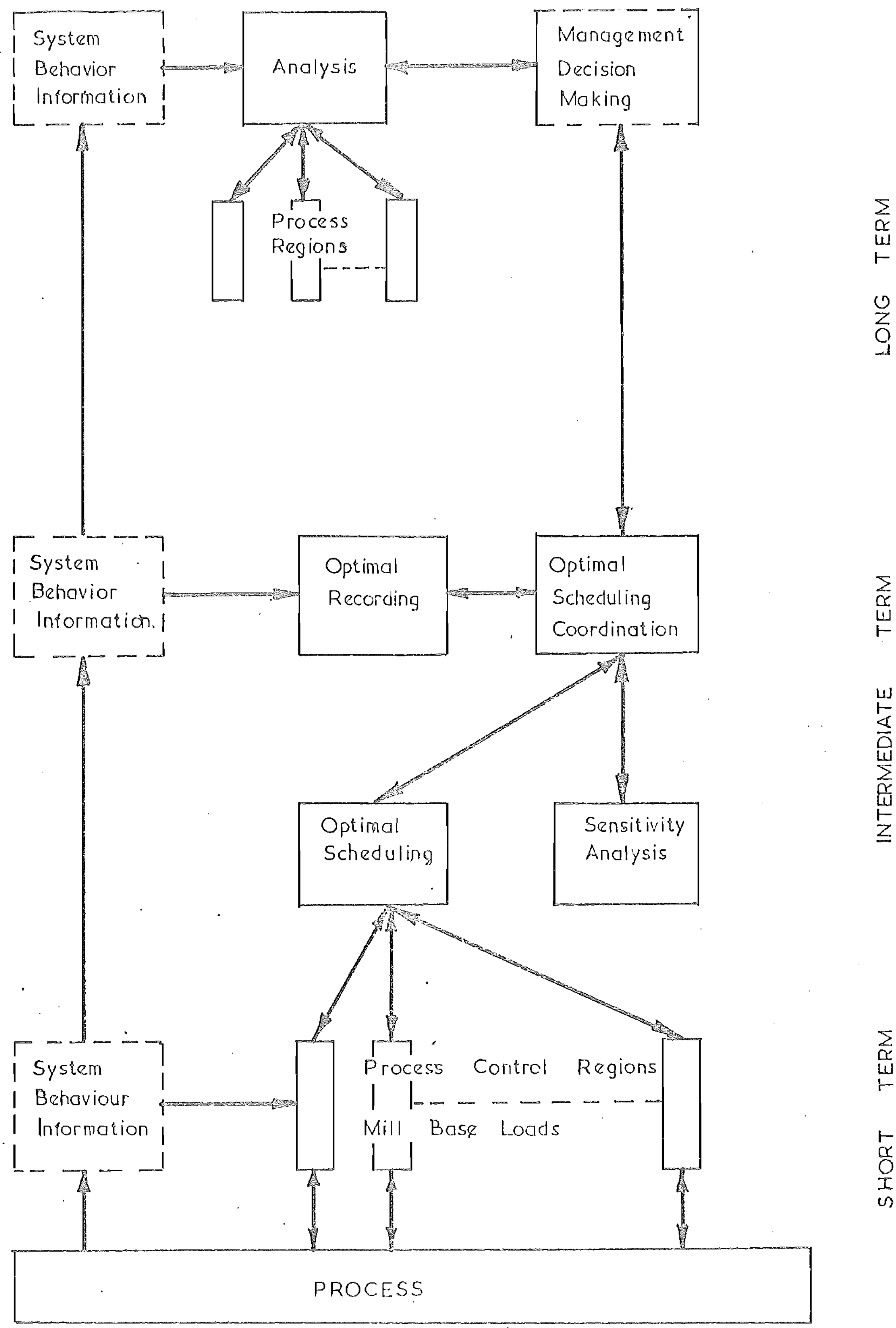


FIG. 2.7 ENERGY OPTIMISATION — PROBLEM DECOMPOSITION

2.3.2 Further Definition of the Energy Optimisation Subproblem Restraints Yeilding Specifications for Suitable Algorithms

Two factors influence the choice of algorithm at each level, viz: 1) information of system behaviour, and 2) system dynamics.

Considering system dynamics, a broad classification into two groupings is possible:

(1) Fast response units. Those units which respond to disturbances within a few minutes. Most machine units in the system fall into this category. e.g. paper machines, grinders, power boilers, turbines.

(2) Slow response units. Those units with dynamic responses of the order of hours. This category accounts for the product or material storage units - where the comparatively slow speed of response is determined by saturation of finite supply and demand facilities e.g. groundwood storage.

The influences of system information, and system dynamics at each level of the control hierarchy may be summarised:

(i) Long Term

System information at this level is given predominently by reasonably accurate forecasts and probability distributions, as well as deterministic intervention from the upper long term planning sub-level. In terms of the energy optimization study, the analysis task at this level is to determine the minimum cost system (restraints) which will satisfy process demands for some given % of the time. The iterative system shown in Figure 2.8 solves this problem. The solution proceedure may be summarized:

(a) Given forecasts of system behaviour (e.g. paper machine requirements, groundwood unit efficiency etc.) for the coming period in the form of probability distributions, determine the optimal system configuration to satisfy the forecast mean value requirements.

This gives initial values of system parameters (i.e. restraint limitations such as turbo generator capacity, groundwood unit capacity etc).

(b) Using these values of system parameters, determine the cost sensitivity to variation in parameter values (independent variables x), and variation in system behaviour (independent variables y). This sensitivity is given by ∂(total period cost)/ ∂x, and ∂(total period cost)/ ∂y, respectively, and describes the "peakness" in the functional value topology at the optimum point.

(c) Using the same information, determine the likelihood of not meeting production demands.

(d) Submit the resultant information to management. Depending on sensitivity information, and the cost of implementing system parameter changes from present system values (when compared with the resulting operational savings), some variations in system parameter values may be suggested.

(e) Repeat the process from (a), constraining the parameter values to those suggested by management. When all parameter values and sensitivity results are acceptable, the process has converged.

The adaptive nature of the problem requires a high degree of operator intervention in this loop iterative process.

Periods of interest at this level are sufficiently long that in terms of control the slow and fast response system dynamics may be neglected. Various system parameters however, affect the dynamics of the system, particularly the slow response dynamics (e.g. the spare capacity of the electrical network influences the rate at which groundwood pulp can be produced - and thus the time taken to achieve a certain upward change in storage level). Change in the slow response dynamics (i.e. the intermediate storage units) affects the ability of the system to absorb peak demands. This direct relationship between certain system parameter values, system dynamics, and the likelihood of not meeting production requirements must be implicitly considered in the constraint sensitivity analysis as shown in Figure 2.8

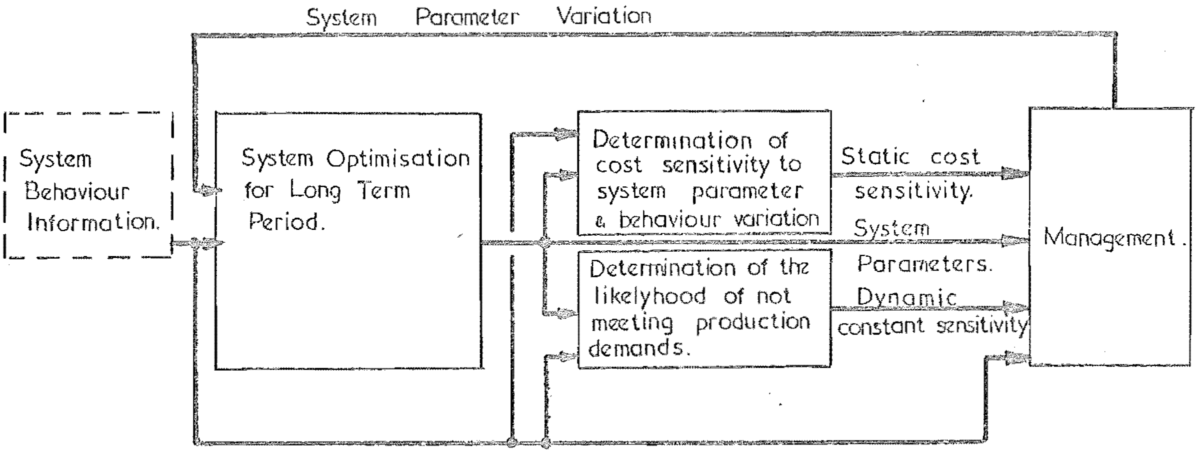


FIG. 2·8 LONG TERM LAYER ITERATIVE SOLUTION PROCESS.

The iterative process described has the computational advantages of static optimisation techniques but implicitly considers the operational dynamics of the system.

(ii) Intermediate Term

Algorithms at this level must consider the slow response system dynamics implicitly, as periods of interest are of the same order, although fast response dynamics may be neglected, as in the long term case. Considering the two related energy optimisation subproblems at this level:

(a) Optimal reordering. This problem involves formulation of optimum decision rules for restocking supplies of each system input material. Such formulations generally involve determination of optimal reorder levels based on: 1) delivery time following the ordering action; 2) material cost; 3) cost of storage; 4) cost of capital required (interest rate), and 5) demand distributions for the coming period.

As predicted information on deterministic system behaviour is not utilized, and demand distributions generally change slowly with time, decision rules derived require updating at relatively infrequent intervals. Formulation of a decision rule for a particular reordering subproblem is therefore an off-line procedure.

(b) Optimal scheduling. Explicit consideration of slow response dynamics requires that the decomposed sub-problem algorithms of this overall problem include 1) dynamic optimisation of energy usage using the expected time-dependent system demands (deterministic information); and 2) analysis of the cost and constraint sensitivity of the resultant optimal trajectories (schedules) with respect to system disturbances which may occur (probabilistic information).

When a non expected system disturbance occurs, trajectories previously produced by the scheduling unit are no longer optimal. The dynamic optimisation of this unit must therefore be capable of rapid updating to produce new optimal trajectories - in the extreme the method must be capable of on-line implementation.

Co-ordination of the two subproblems can be achieved by an iterative procedure as in Figure 2.9. Optimum trajectories are subjected to a sensitivity analysis to determine intervals where the cost sensitivity is high, or where the likelihood of not meeting system demands is high (constraint sensitivity). Artificial constraints are then chosen for these regions to force the trajectory into areas of lesser sensitivity.

Constraint sensitivity is more important than cost sensitivity at this level, as the cost of lost production far exceeds the typical energy saving. Consequently in early schemes cost sensitivity is neglected. Later development, however, enables determination of this parameter. Finally, an algorithm is proposed for the monolithic solution of the overall problem.

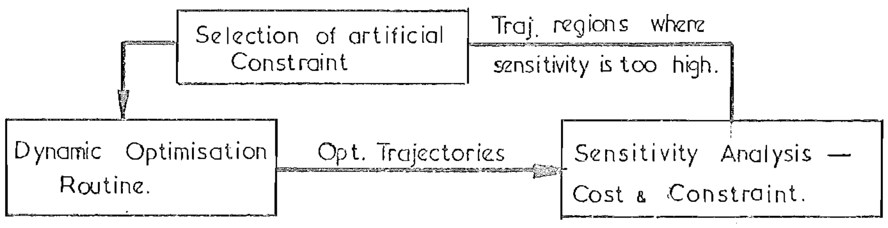


FIG. 2·9 SCHEDULING PROBLEM ITERATIVE COORDINATION

(iii) Short Term

Algorithms at this level are concerned with the optimisation of decomposed sub areas of the system model. Storage units which interface these sub areas need not be considered implicitly in those algorithms as they are accounted for in the co-ordinating scheduling problem of the intermediate level. The order of solution frequency however, requires treatment of major slow response and fast response dynamics internal to the sub region considered: algorithms therefore usually involve dynamic optimisation.

Features similar to the intermediate term case (ii) are:

(a) Utilisation of deterministic and probabilistic information on system behaviour by defining optimisation and sensitivity analysis units for each sub region.

(b) The co-ordination of these two sub problems.

(c) The requirement for on-line algorithms imposed by the high frequency of solutions required, and by the occurrence of unexpected system disturbances.

It is proposed that co-ordination of the decomposed system sub problems could be achieved by a method similar to that proposed by Findeisen (27), as follows:

Define co-ordination variables v, as all variables which interact with other sub systems (this includes variables which interact with the co-ordinating energy network).

In the general case there will be three vector variables:

$\bar{v}_1$ = sub system input quantity and quality variables.
$\bar{v}_2$ = sub system output quantity and quality variables.
$\bar{v}_3$ = sub system energy input variables

i.e. the sub system shown in Figure 2.10.

The sub system optimisation algorithm will utilise internal independent variables to produce a relationship between the co-ordination variables which is optimal in terms of energy usage, subject to system constraints such as quality requirements. This optimal relationship $f^* (\bar{v}_1, \bar{v}_2, \bar{v}_3)$ is shown as a family of curves for the case where $\bar{\bar{v}}_1 = v_1$, $\bar{\bar{v}}_2 = v_2$, and $\bar{\bar{v}}_3 = v_3$, (see Figure 2.11)

The relationships $f^* (\bar{v}_1, \bar{v}_2, \bar{v}_3)$ can be considered as the internally optimal transfer functions for the sub systems. The scheduling and co-ordination algorithm of the intermediate level then utilises these transfer functions to arrive at a globally optimal schedule. These schedules define the optimal values of $\bar{v}$, i.e. define the control action at the lower short term level.

Quality variables can be constrained above certain values, or may be included in the upper and/or lower functional equations.

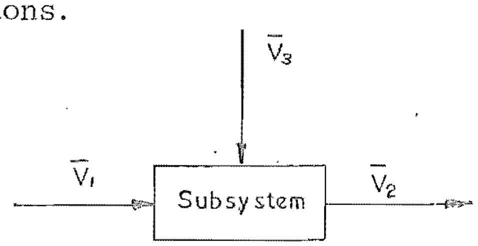


FIG. 2·10 SHORT TERM PROCESS OPTIMISATION SUBSYSTEM & INTERACTION

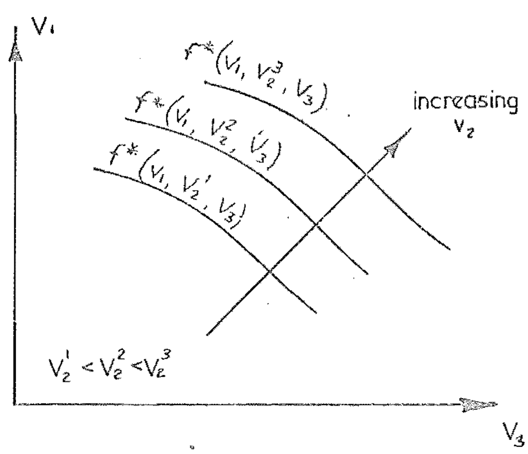


FIG. 2·11 A FAMILY OF OPTIMAL SUBSYSTEM TRANSFER FUNCTIONS.

Where the optimal transfer functions are not subject to rapid variation, co-ordination may be carried out over periods which are some multiple of the intervals considered at the lower level, i.e. the solution frequency of the supremal is less than that for the infimal (as implied in the layer structure of this study). If however, the optimal transfer functions change more rapidly, then obviously co-ordination must be carried out at the same frequency as the lower level process optimisation.

At this stage, it is not proposed that process optimisation algorithms be developed, owing to the lack of data and specialist process knowledge. Units at this level are therefore treated as: 1) individual process units, in which case the co-ordination variables are related by the "best" transfer function possible with manual control; 2) mill base loads, when the co-ordination variable is fixed equal to the sum of demands; and 3) inter-process region storage, when the co-ordination variable is the storage level.

The total energy optimisation problem decomposition and the required algorithm specifications for each level, are summarised in Figure 2.12.

2.4 DEVELOPMENT OF SUITABLE MODELS FOR THE ENERGY OPTIMISATION STUDY

There are two aspects to the modelling task.

The first is concerned with determination of an overall model for the system to be controlled: this model will have a macro variable system-wide nature consistent with the discussions of Chapter 1. The model will not be final in the sense that it serves only as a basis for the study in general, thus it must permit more detailed expansion of desired regions.

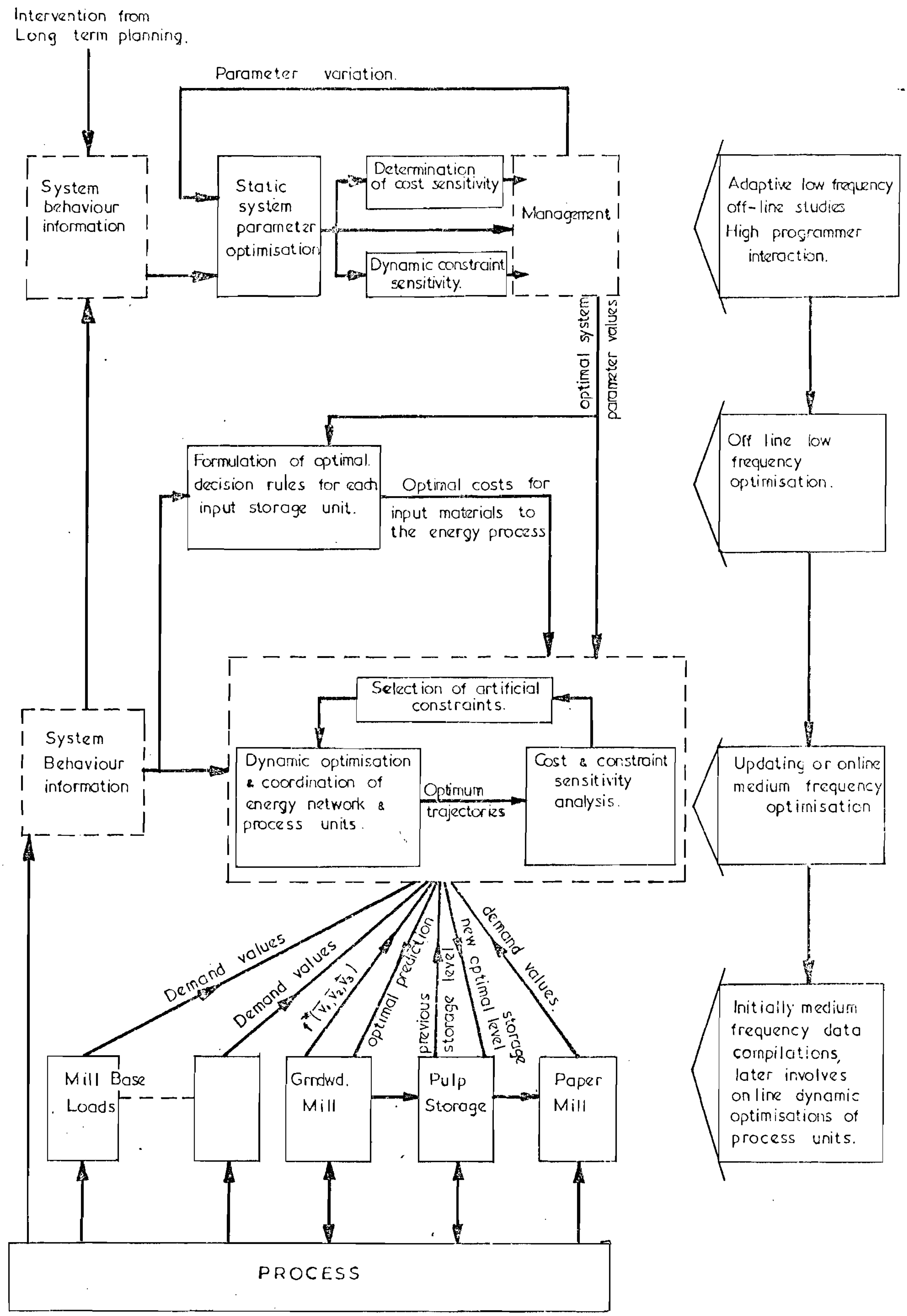


FIG. 2·12 ENERGY OPTIMISATION PROBLEM DECOMPOSITION AND ALGORITHM SPECIFICATION.

The second aspect is concerned with investigation and modelling of the disturbances the system is liable to undergo. Work here is of a preliminary nature as the large amounts of data and time necessary are not available at this stage.

2.4.1 Models of System Structure

The modelling policy utilised here is one of "aggregation" (1, 38, 39). This policy results in description of the system by a lower order model such that the model variables in some given sense represent macro-variable "averages" of the system variables. Thus sections of the process are defined by an "index function" f, such that for every t, f(t) depends on the instantaneous values of all variables $x_1(t)$, $x_2(t), \ldots\ldots\ldots$ $x_n(t)$.

$f(t) = F(x_1(t)\ x_2(t)\ \ldots\ldots\ldots\ldots,\ x_n(t))$ thus represents an index of system behaviour with time.

This type of macro variable has been used in stability studies of large systems (Lyapunov functions) (1), and, with respect to the present study, has the following advantages:

(i) aggregation can be performed in several stages resulting in a hierarchy of models, the aggregate variables describing appropriate performance for each level. This permits a ready decomposition to a lower level if greater detail is required at any stage.

(ii) The index function could be the instantaneous value of a performance function for a local process unit optimisation, thus permitting sub-optimisation of process units as discussed in 2.3. Co-ordination of these sub-optimisations is then the function of the overall optimisation.

(iii) The decomposition of the system into operational areas, or process units, provides a ready basis for aggregation.

2.4.1.1 Model Aggregation Step 1

With respect to the process schematic of Figure 2.1 (a repeat of Fig. 1.4), several simplifying observations may be made:

(i) Logging operations are not connected to the system in an energy sense, and the connection in the process sense is highly buffered by storage at the mill. Consequently, for normal operation the effect of logging operations may be neglected.

(ii) Finishing and Shipping of the final products are principally accounting functions and have minimal interaction with the process or energy systems. These functions may thus be neglected.

(iii) The stock preparation activity is approximately proportional to paper machine production as the connecting storage is small. These two process units may thus be combined into a single unit.

(iv) In terms of the energy system, the sawmill and timber treatment sections may be treated as a composite unit, the latter especially having minor energy requirements.

(v) The chemical pulping cycle is dependent principally on pulp production, the black liquor and white liquor storage being minimised with respect to production requirements only so as to reduce the quantity of constituent chemicals required. As little flexibility is designed into the cycle for the purposes of energy supply and demand regulation, it was considered that attempts to impose this form of control would either be injurious to product quality, or would result in greater chemical loss. Similarly, the addition of oil to the recovery boilers to boost steam output was not an allowed variable in the energy optimisation as:

   (a) it is detrimental to the chemical recovery process.

   (b) additional steam required can be produced by the power boilers.

As a result of these considerations it was decided to treat the cycle as a single equivalent process unit at this stage. Although the recovery boiler is included schematically in the steam plant, its output was taken as proportional to the production of the chemical pulping unit.

(vi) As optimisation of either quality or energy usage within the groundwood sub system is not within the scope of this project, at least initially, no loss is incurred by treating the sub system as an equivalent unit in terms of the overall energy optimisation. Flows of white water, and caustic soda are small compared to amounts available; it was thus assumed that groundwood requirements for these could be met at all times. The efficiency (energy/production) of this composite unit is critically dependent on internal quality considerations. As this unit is a major electricity consumer, a more detailed representation may be required at a later stage, however, this section of the aggregated model may always be expanded.

2.4.1.2 Model Aggregation Step 2

The next aggregation step is concerned with identifying process units which may be readily, or usefully controlled with regard to energy optimization. Units which do not fall into this category may then be aggregated into "block" energy requirements, or "mill base loads", corresponding to the energy distribution forms. Process storage units are also considered with regard to:

(i) "equivalent energy" storage capacity. This is a function of energy required/ton of the product stored and ton storage capacity. Stored energy of this form can be useful in times of peak energy demands, in that the preceeding plant unit can be operated under reduced throughput, thus releasing energy for use elsewhere. If a storage unit and the preceeding process units are to be operated in this manner, it is preferable that the process units have a high consumption of an energy form of limited availability (due to energy system constraints), and that the process units be themselves preceeded by a large storage to absorb production of earlier units, otherwise large sections of the plant might be forced to reduced throughput.

(ii) The "period of discharge" of the storage unit. This is a measure of the effectiveness of buffering the unit and is the time taken for the storage level to fall from maximum to minimum levels whilst under normal operation conditions but with no input to the store. If this period is short the effectiveness of energy control storage is limited, and special monitoring or control may be required even if energy control is not proposed.

The various blocks and interconnections of Figure 2.1 and the steam distribution schematic of Figure 2.13 are therefore examined with respect to the nature and magnitude of their loading, productions or storages as follows:

1. <u>Energy Supply and Distribution System</u>

Within this system, the following simplifications can be made:

(i) Including 650 psi outputs of the recovery boilers as negative components of a unit base load (MBL 650). Support units of these boilers (e.g. air fans, water pumps, soot blowers, etc.) are included as positive components of the corresponding mill base loads (MBLE, MBL 650). As the recovery boilers are process dependent, little flexibility is lost.

(ii) As the three power boilers use similar fuels, have similar performance characteristics and constraints, and all output 650 psi steam, they may be combined into a single composite boiler. For the purposes of this study it is assumed that the three boilers are operated optimally to produce the required output of the "equivalent single boiler". Later work may show the necessity of an optimal controller in this region.

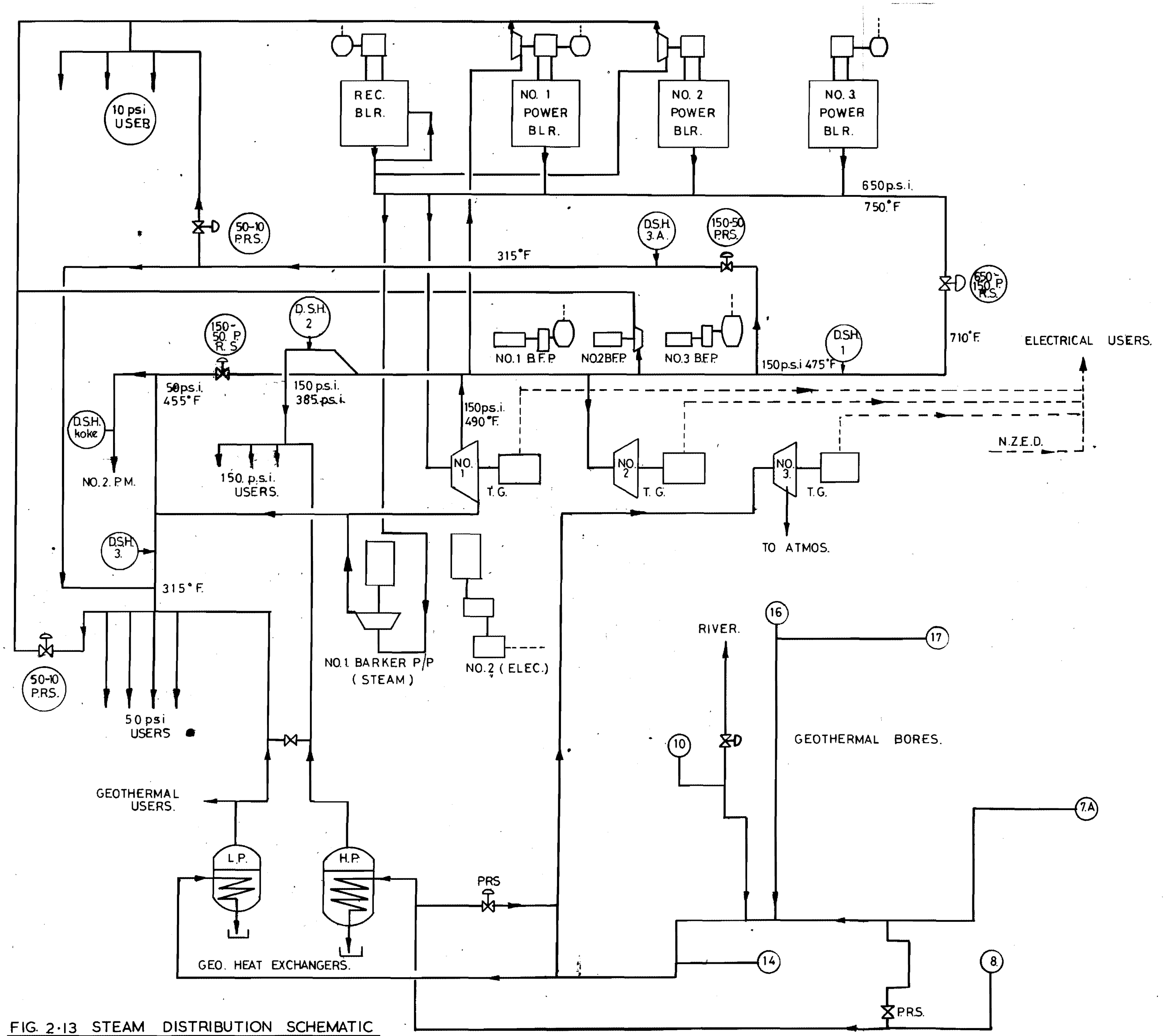


FIG. 2·13 STEAM DISTRIBUTION SCHEMATIC

(iii) Including the boiler support (air fans etc.) requirements for steam and electricity in their respective mill base loads (MBL 150, MBLE). Although these requirements are roughly proportional to boiler output, they are small with respect to the mill base loads, thus the aggregation errors are minor.

(iv) As the 10 psi steam requirement is largely satisfied by the boiler fan exhaust, this level in the hierarchy can be removed. Makeup steam demands through the 50/10 psi passive reducing station are low, and are thus absorbed in the 50 psi mill base load with little effect.

(v) Turbines, heat exchangers, passive reducing stations, and N.Z.E.D. supply have been considered as separate units owing to different characteristics, costings or restraints.

2. Water Treatment

The inputs to this block are principally river water and electricity, the output being filtered water for general mill use or highly purified water for use in boilers. Although daily water consumption is high (24 million gallons/day), adequate river supply is always available so large storage is not necessary. The electrical loading of this section is comparatively modest (1.5 MW average), is reasonably constant (as the major water consumers operate 24 hours/day), and is not readily controllable. We may thus remove this sub system from consideration (assuming water is supplied when required), accounting for the electricity consumption in one of, or a combination of two ways:

(a) Apportioning the electrical load to the various water consumers proportional to their requirements. In general, this can be taken as proportional to production rate.

(b) Including the water treatment electrical load in an "electrical mill base load".

Method (a) is considered to be more physically realistic, however aggregation of other process units tends to reduce method (a) to method (b). Method (b) was thus initially adopted, this having considerable advantage with respect to data acquisition.

3. Input Log Storage

The capacity of this unit is very large to act as a buffer between the mill and logging operations. For normal mill operation, it can be assumed that logs are available when required, i.e. the storage unit can be considered as an infinite source.

4. Wood Preparation

This block requires relatively small amounts of electricity and 150 psi clean steam (average - 1.0 MW and 10,000 lbs/hr), in addition to high pressure water for the hydraulic debarker. The latter demand may either be supplied electrically (1.3 MW) or by a steam turbine (650 psi input, 50 psi output, 30,000 lbs/hr). Because of this flexibility the barker pumps have been considered as separate units in the energy system.

As the other steam and electrical loadings are made up of many small loadings, effective control as part of an optimising scheme would be difficult, and of doubtful value. Accordingly the steam and electrical requirements are included in the respective mill base loads (MBL 150, MBLE).

5. Wood Prep - Sawmill Storage

As this unit has a large "period of discharge", and a relatively small "equivalent energy" capacity, the infinite source assumption with regard to sawmill requirements, and a similar infinite sink assumption with respect to wood preparation output, may safely be made. Thus dependence between the two process units is removed.

6. Sawmill

This is effectively a mill output unit, and is therefore not subject to energy control. Steam and electricity requirements are small (10,000 lbs/hr 100 psi geothermal steam; 13,000 lbs/hr 50 psi clean steam; 1.4 MW electricity), relatively constant although periodic, and made up of multiple small loads. Hence steam and electrical requirements are included in the respective mill base loads (MBLG 100, MBL 50, MBLE).

7. Wood Prep. Sawmill - Steam Plant Storage

This hog fuel storage is directly a source of energy, however two factors mitigate against explicit consideration in the energy control system.

(i) Low energy content/ton as compared to coal or oil. Boiler feed capacities are limited, consequently use of hog fuel during periods of high steam requirement is not considered advisable.

(ii) The storage unit has a high (1 week) period of discharge, consequently infinite source and sink assumptions may be made.

The hog fuel has effectively a negative cost in that non-use would result in heavy removal costs, economy thus demands use of this fuel. Point (ii) allows hog fuel to be considered as available when required.

8. Wood Prep - Sulphate Pulp Unit Storage

The "period of discharge" for this unit is approximately two weeks, and the "specific energy content (= energy/ton) of the stored chips is low. Infinite source and sink assumptions can thus be made, this making the sulphate pulping process independent of earlier stages in the process.

9. Sulphate Pulp Mill

This unit has a medium-high requirement for 150 psi and 50 psi clean steam (63,000 and 52,000 lbs/hr respectively), but a relatively low requirement for electrical energy (2.25 MW). In addition the recovery boilers of this unit have a high output of 650 psi steam, roughly proportional to pulp throughput. Three points mitigate against individual control of this unit.

(i) The plant is usually working at, or near full capacity as excess pulp can be dried and sold as a system output.

(ii) The nature of the energy system is such that in general electrical energy is under the tightest constraints. The small electrical loading of this pulp mill renders control for electrical purposes of doubtful value.

(iii) The 150 and 50 psi steam supply is not so tightly constrained that all normal optimal peak demands cannot be met, although variations in steam cost/lb with load may occur due to the necessity to utilize less efficient conversion equipment. Control of this medium steam usage unit would thus result in relatively minor savings. In addition, throughput reduction would affect recovery steam output after a short time delay, this being detrimental to good chemical recovery. The loss of production steam would have to be made up by the power boilers, effectively wiping out any savings incurred.

Accordingly, the throughput of this unit is not included as a variable in the energy cost optimisation. As the energy requirements are relatively constant, the steam and electrical units are included in the respective mill base loads (MBL 150, MBL 50, MBLE).

10. Sulphate Pulp Mill - Bleach Plant, Flakt Dryer Storage

This unbleached pulp store has a low "period of discharge", and medium "equivalent steam energy" storage. Due to the considerations above, this unit and the preceeding mill are not controlled individually. The level in this storage unit will affect process throughput of the sulphate pulp mill and the bleach plant (assuming that the output dryer unit will work to full capacity) as infinite source and sink assumptions are not fully justified, however these relatively minor process effects will have little impact on total mill base loads of the energy system. Consequently this storage unit is not featured in the energy system model.

11. Flakt Dryer

This is an output unit and is thus assumed to work to capacity subservient to the pulp requirements of the paper machines. It is a relatively small electricity consumer (0.5 MW), 150 psi steam consumption being medium-low (24,000 lbs/hr). These loadings are constant during operation and are thus considered in the mill base loads (MBLE, MBL 150).

12. Bleach Plant

This unit is a minor steam (7,000 lbs/hr 50 psi) and electricity (1.3 MW) user, consequently it is not considered as an energy variable, especially in view of the slow response imposed by bleach quality considerations. The energy requirements are thus considered in the mill base loads (MBL 50, MBLE).

13. Bleach Plant - Flakt Dryer, Paper Machine Storage

This storage has a "period of discharge" of 3 hours under normal operation, however, as the bleach plant has adequate reserve capacity and bleached pulp is only utilized by the flakt dryer under excess conditions, this unit is assumed to have no effect with respect to either paper machine or energy system operation.

14. Chlorine Plant and Associated Output Storage

The chlorine plant is a medium consumer of electricity (1.9 MW) and 50 psi steam (6,000 tons/hr). The storage for chlorine and caustic soda have a period of discharge of 3 days under average mill conditions, thus this unit is suitable as an energy variable to control peak loads. However, as the chlorine requirements of the bleach plant may vary considerably, and chlorine plant output capability also varies due to maintenance difficulties, it was decided not to utilise this production variable in the energy optimisation at this stage. The energy requirement was therefore included in the mill base loads (MBLE and MBL 50).

15. Wood Preparation Groundwood Mill Storage

This storage is divided into two sections. The major storage unit has a long period of storage (one week), and the specific energy content of the stored wood billets is low. Infinite source and sink assumptions can thus be made for this section, this achieving independence of groundwood control from earlier process areas. Between this major storage and the groundwood mill, there is a small storage unit (period of discharge - 15 mins) as provision against small conveyor breakdowns. As these are relatively frequent and cannot always be controlled by the storage the resultant production loss should be considered in the optimizing scheme.

16. Groundwood Mill

This unit is a large consumer of electricity (34 MW), and has buffer storage following. Production is thus controllable subject to internal quality constraints. As a first approximation, the eleven grinders and support equipment may be considered as a single large grinder unit with a composite efficiency characteristic. This has the following advantages:

(i) allows the groundwood department greater flexibility for quality control

(ii) averaging the grinder characteristics tends to reduce the variations which can occur

(iii) only one more variable is introduced into the energy system optimisation.

17. <u>Groundwood Mill - Paper Mill Storage</u>

This unit has high equivalent electrical energy storage (120 MWH) but a relatively low period of discharge (4 hours). The maximum and minimum allowable levels are 200 and 90 tons, the latter limit being set through quality considerations. The low period of discharge requires that the storage level be considered explicitly in control of groundwood production.

18. <u>Paper Mill</u>

The two paper machines are of crucial importance within the system. Because of their importance, and their high total consumption of pulp (25 tons/hour), electricity (15.0 MW) and steam (182,000 lbs/hr 50 psi, 4,000 lbs/hr 150 psi) these machines are considered individually in the model. Steam and electricity supplies to the machines are also considered distinct from the mill base loads, the loads being taken as a first approximation, as directly proportional to the paper production.
The production of broke may vary considerably about the average (5 tons/hour) depending largely on paper machine running conditions. Large storage units are available however (150 tons); the % of broke in the prepared stock for the machines may thus be kept relatively constant. Also, broke is available for the groundwood department for freeness control as required. The broke cycle may thus be removed from the model with little effect, by making infinite sink and source assumptions.

The above aggregation and controllability considerations give rise to the system model shown in Figure 2.14.

It may be expected that study at the firm will reveal areas where more detail can be utilised with respect to power optimisation, such as:

(i) groundwood mill
(ii) log storage
(iii) power boiler control
(iv) stock preparation - broke return systems
(v) chlorine plant

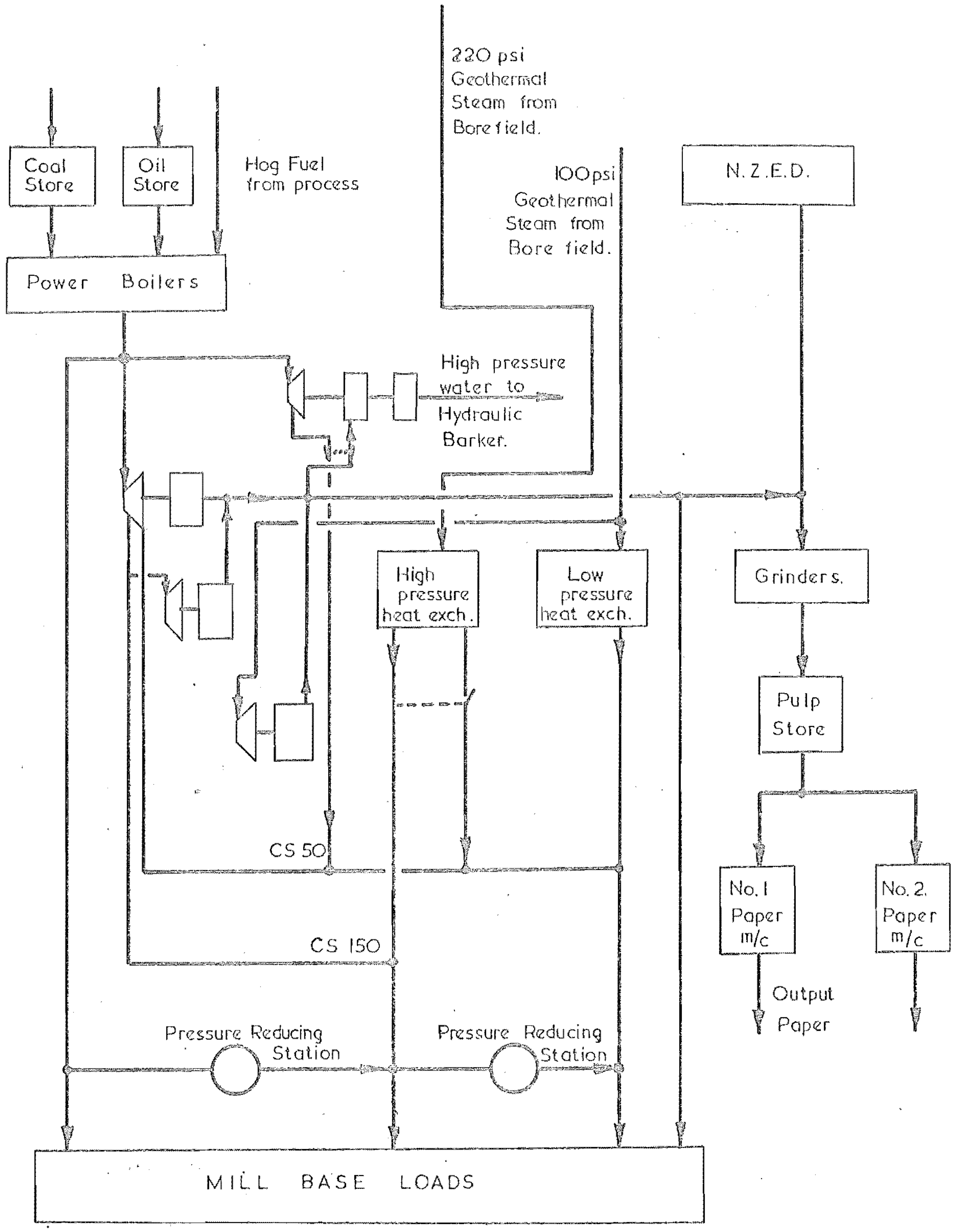


FIG. 2.14 SCHEMATIC OF THE AGGREGATED MODEL

At this stage, however, the model is a satisfactory representation of a complex system, and can always be extended later into a hierarchical structure to include more detail.

2.4.1.3 Separation of Input Storage from the Model

The input storage units of the system (for coal, oil and chemicals) are designed to act as a buffer between the relatively continuous process demands, and the discontinuous arrival of the inputs, generally bulk purchased and transported by truck or rail. Consequently these units have periods of discharge of several weeks.

It can be reasonably assumed that reordering and supply of the input quantities will be such that the input storage is never depleted, i.e. the system demands can always be met. With regard to the system energy optimisation, the input storage units may therefore be regarded as infinite sources, and need not be considered explicitly. The optimal reordering of stocks (inventory control) with respect to system demands, input material prices, storage and transportation costs, will not interact directly with the energy system optimisation, although it will influence the overall cost of coal and oil. The two problems may thus be considered separately.

The simple storage model of the optimal reordering problem is shown in Figure 2.15. The simplified "working" model for the energy optimisation problem is featured in Figure 2.16. Tables 2.1, 2.2 and 2.3 give the key to this diagram.

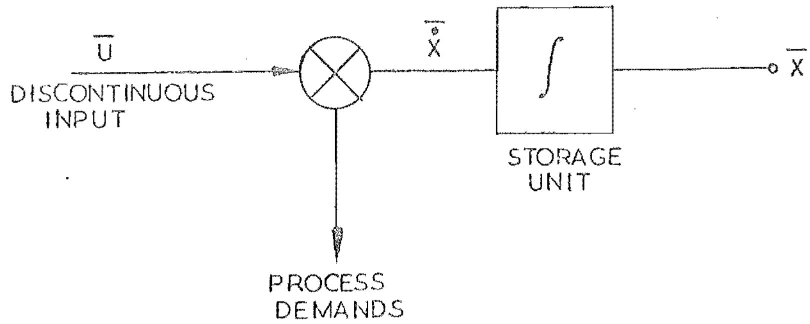


FIG. 2·15 SIMPLE STORAGE MODEL FOR THE OPTIMAL RE-ORDERING PROBLEM

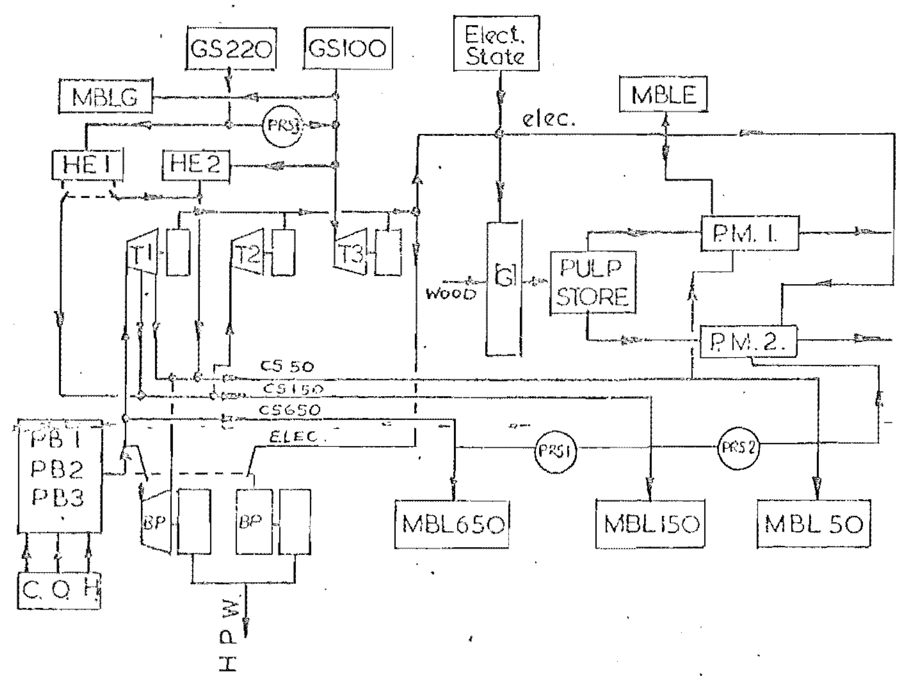


FIG. 2·16 ENERGY OPTIMISATION MODEL

Table 2.1 Model Energy Sources

Energy Sources	Symbol	Distribution Forms	Symbol
Geothermal steam at 100 lb/in^2	GS100	650 lb/in^2 clean steam	CS650
Geothermal steam at 220 lb/in^2	GS220	150 lb/in^2 clean steam	CS150
Coal fuel for power boilers	C	50 lb/in^2 clean steam	CS50
Oil fuel for power boilers	O	Electrical energy	ELEC
Scrap wood (hog) for power boilers	H		
Process dependent steam (650 lb/in^2) from chemical recovery cycle			
Electrical energy purchased from the state	ELECT STATE		

Table 2.2 Model Energy Converters

Energy Converters	Symbol	Input	Output
1 turbine	T1	650 lb/in^2 clean steam	50; 150 lb/in^2 clean steam and electrical energy
1 turbine	T2	150 lb/in^2 clean steam	Electrical energy
1 turbine	T3	100 lb/in^2 geothermal steam	Electrical energy
1 PRS*	PRS1	650 lb/in^2 clean steam	150 lb/in^2 clean steam
1 PRS	PRS2	150 lb/in^2 clean steam	50 lb/in^2 clean steam
1 PRS	PRS3	220 lb/in^2 geothermal steam	100 lb/in^2 geothermal steam
1 heat exchanger	HE1	220 lb/in^2 geothermal steam	150 or 50 lb/in^2 clean steam
1 heat exchanger	HE2	100 lb/in^2 geothermal steam	50 lb/in^2 clean steam
3 power boilers	PB1 PB2 PB3	Coal, oil, or scrap wood fuel	650 lb/in^2 clean steam

* Pressure reducing station.

Table 2.3 Model Energy Uses

Energy Users	Symbol	Production Requirements
2 paper machines	PM1 PM2	Electricity, pulp, and 50 lb/in^2 clean steam
2 Barker pumps	BP	Either electricity or 650 lb/in^2 steam
11 grinders	G	Electricity and wood
Electrical mill base load	MBLE	Electricity
650 lb/in^2 clean steam mill base load	MBL650	650 lb/in^2 clean steam
150 lb/in^2 clean steam mill base load	MBL150	150 lb/in^2 clean steam
50 lb/in^2 clean steam mill base load	MBL50	50 lb/in^2 clean steam
100 lb/in^2 geothermal steam mill base load	MBLG	100 lb/in^2 geothermal steam

2.4.1.4 Mathematical Formulation and Objective Function for the Model

With respect to the model of Figure 2.16, the following variables specify the system behaviour at any time (t).

(a) State Variable

$X_1(t)$ = tons of groundwood pulp stored

(b) Control Variables

$U_1(t)$ = production of groundwood mill in tons/hour

$U_2(t)$ = electrical output, No. 2 turbine

$U_3(t)$ = electrical output, No. 3 turbine

$U_4(t)$ = 50 psi output, low pressure heat exchanger

$U_5(t)$ = 50 psi output, high pressure heat exchanger

$U_6(t)$ = 150 psi output, high pressure heat exchanger

$U_7(t)$ = 150 psi output, 650 - 150 psi pressure reducing station

$U_8(t)$ = 50 psi output, 150 - 50 psi pressure reducing station

$U_9(t)$ = 100 psi output, 220 - 100 psi geothermal pressure reducing station

$U_{10}(t)$	= hog fuel input to power boilers
$U_{11}(t)$	= coal fuel input to power boilers
$U_{12}(t)$	= barker pump electrical input
$U_{13}(t)$	= barker pump 650 psi steam input = 50 psi steam output
$U_{14}(t)$	$= 1 \Longrightarrow U_6 = O; \ = 2 \Longrightarrow U_5 = O$
$U_{15}(t)$	$= 1 \Longrightarrow U_{12} = O; \ = 2 \Longrightarrow U_{13} = O$

(c) Dependant Variables $\underset{\sim}{V}$ (t)

$V_1(t)$	= N.Z.E.D. electricity supply
$V_2(t)$	= 100 psi geothermal steam supply
$V_3(t)$	= 220 psi geothermal steam supply
$V_4(t)$	= oil fuel input, power boilers
$V_5(t)$	= 650 psi output, power boilers
$V_6(t)$	= 50 psi output, No. 1 turbine
$V_7(t)$	= 150 psi output, No. 1 turbine
$V_8(t)$	= 650 psi input, No. 1 turbine

(d) System Demands

$Y_1(t)$	= tons/hour output of No. 1 paper machine
$Y_2(t)$	= tons/hour output of No. 2 paper machine
$Y_3(t)$	= electrical mill base load (KW)
$Y_4(t)$	= 650 psi clean steam mill base load (lbs/hr)
$Y_5(t)$	= 150 psi clean steam mill base load (lbs/hr)
$Y_6(t)$	= 50 psi clean steam mill base load (lbs/hr)
$Y_7(t)$	= 100 psi geothermal steam mill base load (lbs/hr)

(e) Transfer Functions

Each of the control units (U) can be expected to have a nonlinear relationship between input and output. No information was available on the nature of this relationship however, and plant experimentation was not feasible, so linear transfer functions, similar to those of Weston (40) were assumed. These may be expressed as a vector $\underset{\sim}{Q}(t)$ of time dependent coefficient values.

(f) System Constraints

The system constraints give the relationship between the dependent and independent variables and are determined by the mill balances.

(i) Pulp Balance

$$X_1(t) = \int \mathring{X}_1(t)\ dt$$

$$\mathring{X}_1(t) = U_1(t) - q_1(t)\ Y_1(t) - q_2(t)\ Y_2(t)$$

(ii) Electricity Balance

$$\text{N.Z.E.D. supply} = V_1(t) = Y_3(t) + U_{12}(t) + q_7(t)\ U_1(t) + q_3(t)\ Y_1(t) + q_4(t)\ Y_2(t) - U_2(t) - U_3(t) - (q_{10}(t)\ V_6(t) + q_{11}(t)\ V_7(t))$$

(iii) 650 psi Clean Steam Balance

$$V_5(t) = Y_4(t) + U_{13}(t) + V_8(t) + q_{15}(t)\ U_7(t)$$

(iv) 150 psi Clean Steam Balance

$$V_7(t) = Y_5(t) + q_9(t)\ U_2(t) + q_{16}(t)\ U_8(t) - U_6(t) - U_7(t)$$

(v) 50 psi Clean Steam Balance

$$V_6(t) = Y_6(t) + q_5(t)\ Y_1(t) + q_6(t)\ Y_2(t) - U_{13}(t) - U_4(t) - U_5(t)$$

(vi) 100 psi Geothermal Steam Balance

$$V_2(t) = Y_7(t) + q_8(t)\ U_3(t) + q_{12}(t)\ U_4(t) - U_9(t)$$

(viii) 220 psi Geothermal Steam Balance

$$V_3(t) = q_{13}(t)\ U_5(t) + q_{14}(t)\ U_6(t) + q_{17}(t)\ U_9(t)$$

(viii) No. 1 Turbine Steam Balance

$$V_8(t) = V_6(t) + V_7(t)$$

(ix) Power Boiler Energy Balance

$$V_5(t) = q_{19}(t)\ U_{10}(t) + q_{18}(t)\ U_{11}(t) + q_{20}(t)\ V_4(t)$$

(g) System Restraints

These may be expressed in vector form as:

$$\underset{-}{X}(t)_{min} \leqslant \underset{-}{X}(t) \leqslant \underset{-}{X}(t)_{max}$$

$$\underset{-}{U}(t)_{min} \leqslant \underset{-}{U}(t) \leqslant \underset{-}{U}(t)_{max}$$

$$\underset{-}{V}(t)_{min} \leqslant \underset{-}{V}(t) \leqslant \underset{-}{V}(t)_{max}$$

(h) Objective Function

All input costs are linear, therefore a row vector of cost coefficients $\underset{-}{C}(t)$ can be formed. All costings are proportional to energy quantity except for electrical energy from the N.Z.E.D., which has an additional charge, $C_6(t)$ for the negotiable maximum demand value $U(t)_{max.}$ The objective function can thus be formed:

$$Z(t) = \int_0^t \left[\sum_{i=1}^{4} C_i(t) V_i(t) + C_5(t) U_{11}(t) + C_6(t) V_1(t)_{max} \right] dt$$

(i) General Formulation

The model under discussion can be imbedded in the more general class of multichannel problem shown in Figure 2.17. Notice that the system demands are represented by $\bar{U}(t)$ in this formulation. The system equations for this system are:

$$X(t) = \int_0^t \mathring{\bar{X}}(t)\, dt$$

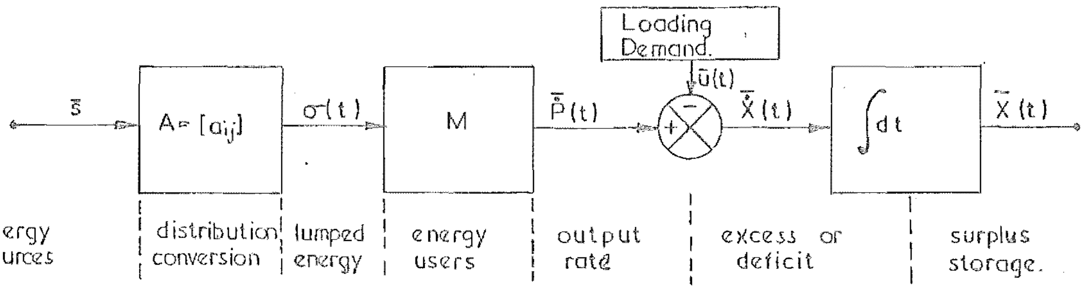
where;

$$\mathring{\bar{X}}(t) = \mathring{\bar{P}}(t) - \bar{U}(t)$$

$$\mathring{\bar{P}}(t) = M\, \bar{\sigma}(t)$$

$$\bar{\sigma}(t) = \bar{A}\, \bar{S}$$

The configuration of the Tasman system under this formulation is shown in Figure 2.18. Tables 2.1, 2.2 and 2.3 give the key to this diagram.



$$A = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & & \vdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix} \quad M = \begin{bmatrix} m_1 & & 0 \\ & \ddots & \\ 0 & & m_n \end{bmatrix} \quad \bar{S} = \begin{bmatrix} s_1 \\ \vdots \\ s_m \end{bmatrix} \bar{\sigma} = \begin{bmatrix} \sigma_1 \\ \vdots \\ \sigma_n \end{bmatrix} \bar{X} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \bar{U} = \begin{bmatrix} u_1 \\ \vdots \\ u_n \end{bmatrix}$$

— FIG. 2·17 A GENERAL MULTICHANNEL SYSTEM —

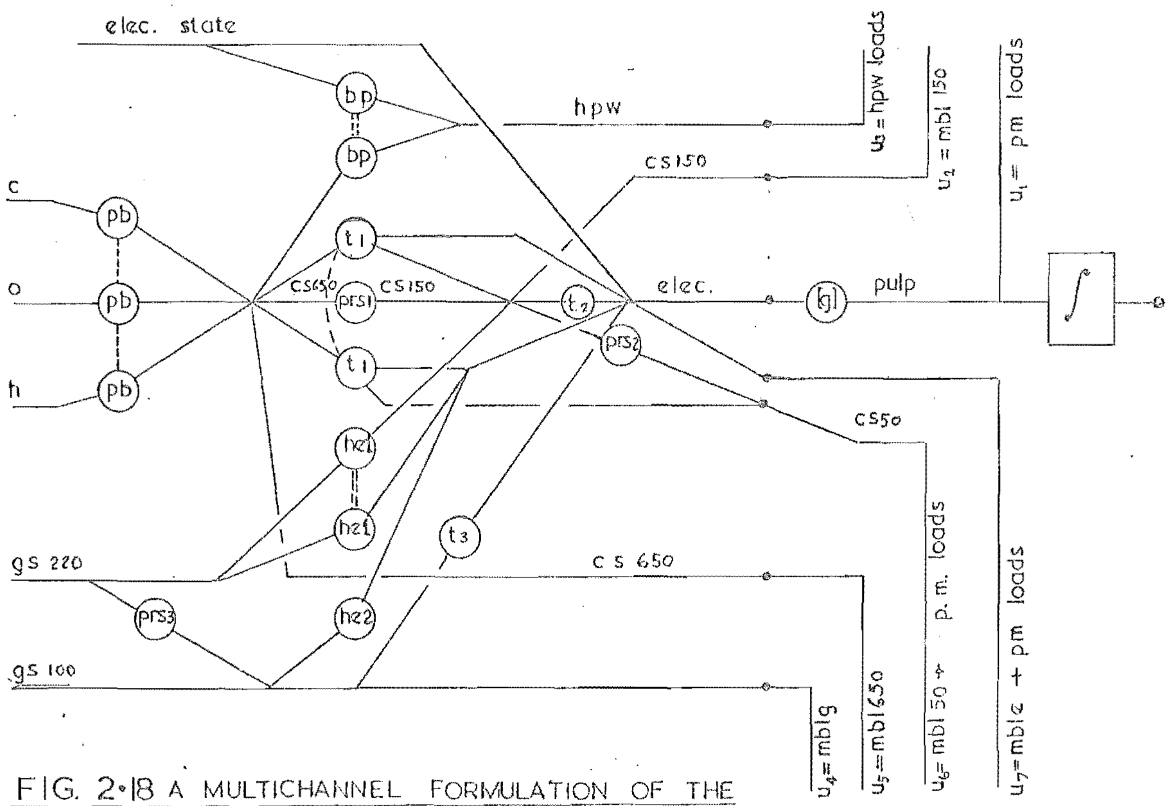


FIG. 2·18 A MULTICHANNEL FORMULATION OF THE ENERGY OPTIMISATION MODEL.

(j) Model Normal Restraint and Coefficient Values

Values have been obtained from various Tasman reports and memoranda, from "Tasman Operating Statistics, 1968", and from personal communication with system operators and engineers.

$X_1(t)_{max}$	= 200 tons	$X_1(t)_{min}$	= 90 tons
$U_1(t)_{max}$	= 22.7 tons/hour	$U_1(t)_{min}$	= 0 tons/hour
$U_2(t)_{max}$	= 2,800 KW	$U_2(t)_{min}$	= 0 KW
$U_3(t)_{max}$	= 9,200 KW	$U_3(t)_{min}$	= 0 KW
$U_4(t)_{max}$	= 50,000 lbs/hr	$U_4(t)_{min}$	= 0 lbs/hour
$U_5(t)_{max}$	= 60,000 lbs/hr	$U_5(t)_{min}$	= 0 lbs/hour
$U_6(t)_{max}$	= 45,000 lbs/hr	$U_6(t)_{min}$	= 0 lbs/hour
$U_7(t)_{max}$	= 600,000 lbs/hr	$U_7(t)_{min}$	= 0 lbs/hour
$U_8(t)_{max}$	= 250,000 lbs/hr	$U_8(t)_{min}$	= 0 lbs/hour
$U_9(t)_{max}$	= 250,000 lbs/hr	$U_9(t)_{min}$	= 0 lbs/hour
$U_{10}(t)_{max}$	= 35,000 lbs/hr	$U_{10}(t)_{min}$	= 0 lbs/hour
$U_{11}(t)_{max}$	= 20,000 lbs/hr	$U_{11}(t)_{min}$	= 0 lbs/hour
$U_{12}(t)$	= 1,300 KW		
$U_{13}(t)$	= 33,000 lbs/hr		

$V_1(t)_{max}$	= 46,200 KW	$V_2(t)_{max}$	= 240,000 lbs/hr
$V_3(t)_{max}$	= 130,000 lbs/hr	$V_4(t)_{max}$	= 12,000 lbs/hr
$V_5(t)_{max}$	= 450,000 lbs/hr	$V_6(t)_{max}$	= 230,000 lbs/hr
$V_7(t)_{max}$	= 85,000 lbs/hr	$V_8(t)_{max}$	= 315,000 lbs/hr

$q_1(t)$	= 0.848 tons/ton	$q_2(t)$	= 0.848 tons/ton
$q_3(t)$	= 598 KWH/ton	$q_4(t)$	= 580 KWH/ton
$q_5(t)$	= 6,944 lbs/ton	$q_6(t)$	= 6,093 lbs/ton
$q_7(t)$	= 1,200 KWH/ton average	$q_8(t)$	= 24 lbs/KWH
$q_9(t)$	= 12.8 lbs/KWH	$q_{10}(t)$	= 0.0462 KWH/lb
$q_{11}(t)$	= 0.0271 KWH/lb	$q_{12}(t)$	= 1.22 lb/lb
$q_{13}(t)$	= 1.22 lb/lb	$q_{14}(t)$	= 1.22 lb/lb
$q_{15}(t)$	= 0.91 lb/lb	$q_{16}(t)$	= 0.937 lb/lb
$q_{17}(t)$	= 0.93 lb/lb	$q_{18}(t)$	= 7.5 lb/lb
$q_{19}(t)$	= 1.7 lb/lb	$q_{20}(t)$	= 7.5 lb/lb

2.4.1.5 Hierarchical Representation of Models

The aggregation and separation processes carried out above give two equivalent hierarchical model structures.

Aggregation Step 1 and separation of input storage result in the general control application hierarchy of Figure 2.19. The upper level of the structure contains management models, and involves total co-ordination of system operations. This level is not considered explicitly in the work of later sections as it is not within the scope of the project. The second level of this structure co-ordinates the energy optimisation, and optimal reordering models. i.e. This level contains the energy network, and the relationships between the various input storage units. The third level contains process unit models to the detail required for individual control tasks. These models may be decomposed to even lower levels of detail if desired, as indicated. Lower levels would correspond to models of particular machine units within the process unit, co-ordination of these models being carried out at level 3.

This model structure may be used for other control applications, necessary model co-ordination being inserted at the required levels. e.g. A task requiring control over several inter related process units would have a co-ordination model at level 2 or superimposed between levels 2 and 3. Energy considerations co-ordinate all process units in the mill; thus the energy co-ordination is at the uppermost level.

This model structure displays the characteristics of a multilevel hierarchical structure (1);

(i) Vertical Decomposition: in that the system is decomposed into a vertical arrangement of sub-systems. The structure of Figure 2.19 also displays horizontal decomposition of levels, thus giving rise to the pyramid like "organizational" hierarchy.

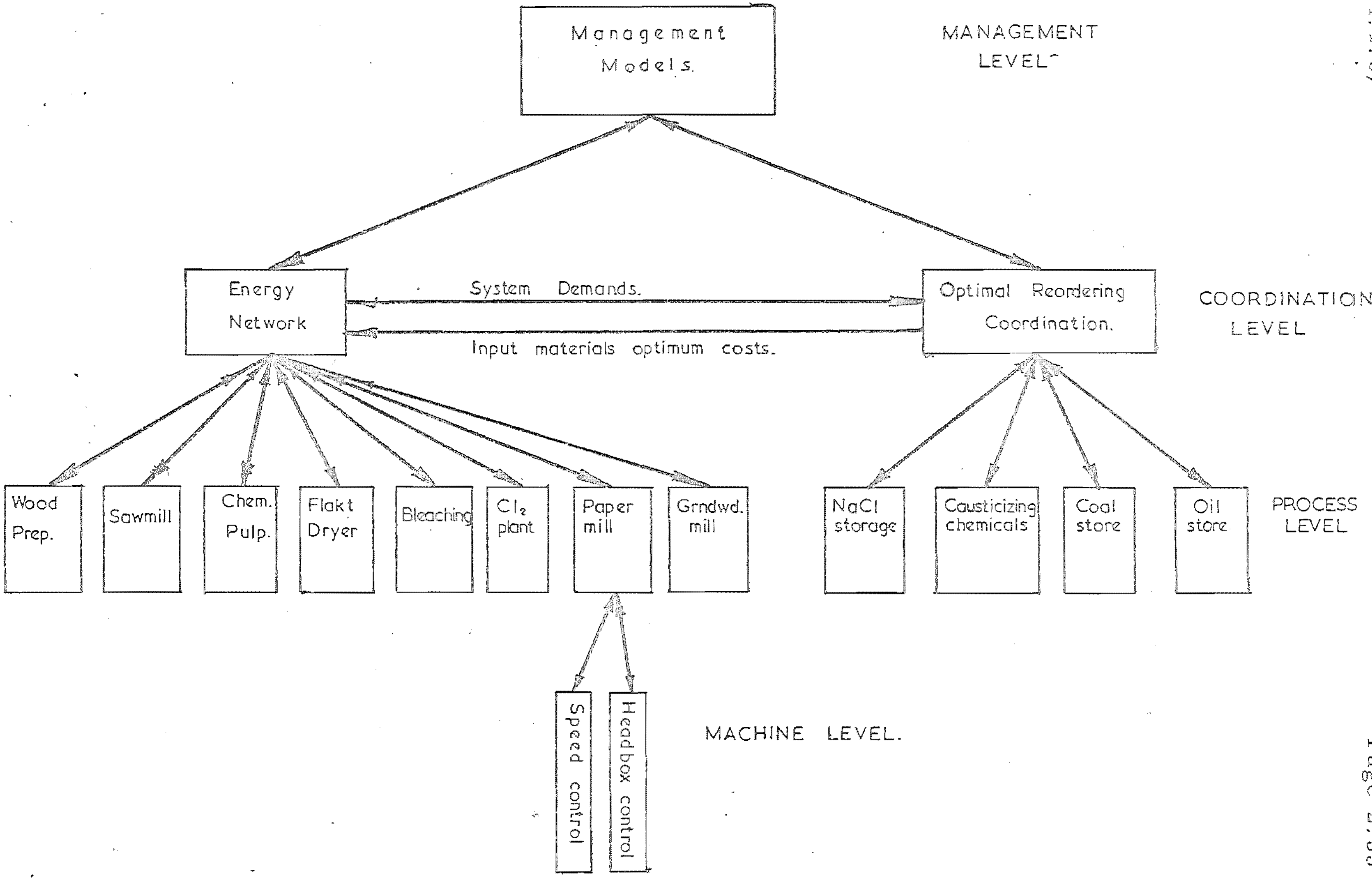


FIG. 2.19 GENERAL MODEL HIERARCHY

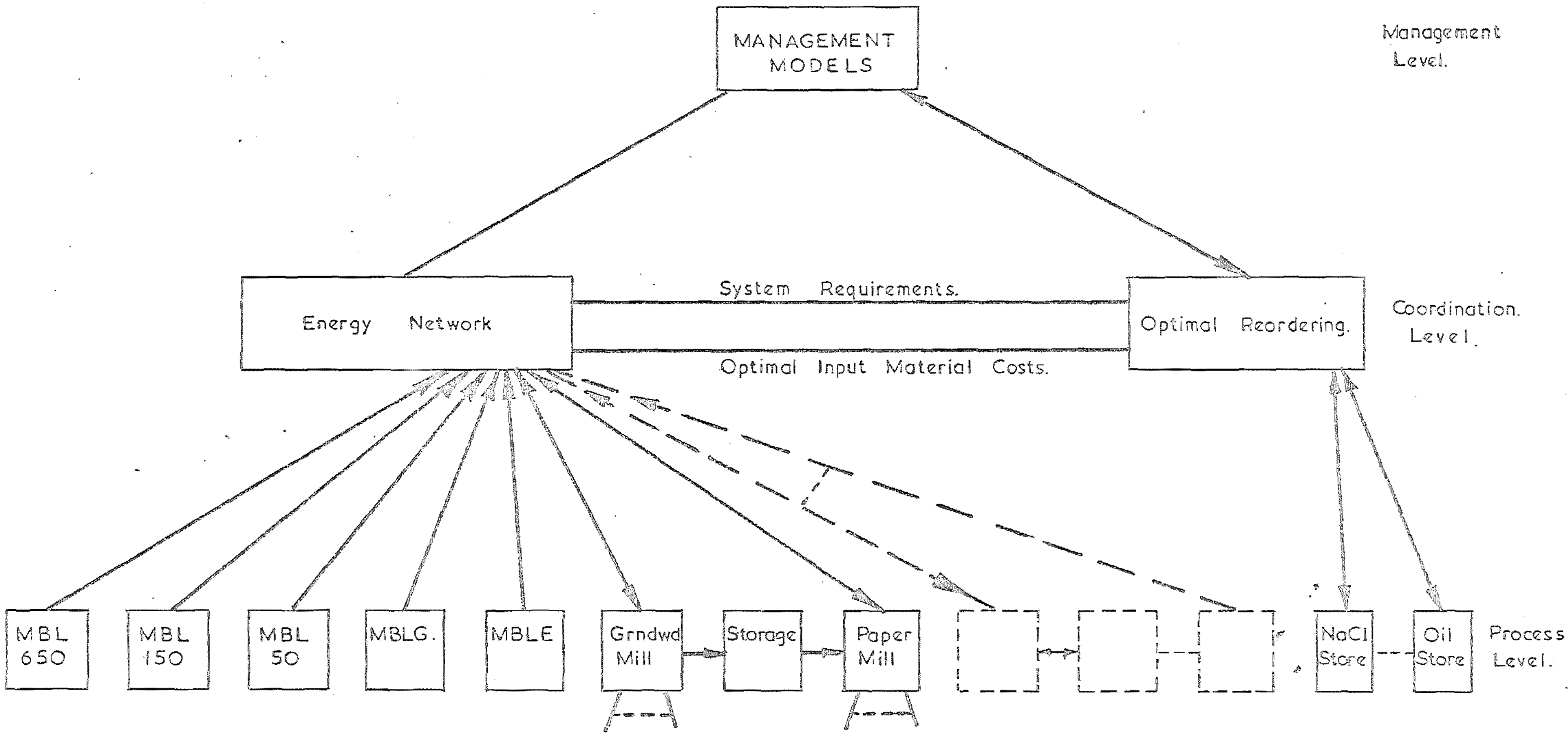


FIG. 2.20 ENERGY OPTIMISATION MODEL HIERARCHY.

(ii) Priority of Action: in that the operation on any level is influenced directly and explicitly from higher levels. This intervention reflects the priority of actions and goals of the higher levels.

(iii) Performance Interdependence: Although the priority of action is oriented downward, the success of the overall system depends on the performance of all units in the system. Since (ii) assumes that intervention precedes action at any level, the success of higher level units depends on the performance at lower levels. Performance can thus be considered as an upward feedback response to intervention.

Aggregation step 2 reduces the general model structure of Figure 2.19 to a particular model hierarchy for the energy optimisation problem, Figure 2.20. This structure has the aggregated energy loads, and the two process units for individual consideration at the lower level. Generalization to the degree required may be achieved by removing process units of interest from the "mill base loads" or featuring them individually at the same level, i.e. reverting to the form of Figure 2.19. As with the previous structure, decomposition of individual process units to give greater detail is possible if required.

The aggregation and separation policies followed have resulted in a multi level hierarchical model, which, while being a minimum variable model for the energy optimization problem, is also expandable to include more detailed considerations for this, or other problems. The model thus satisfies the requirements of Chapter 1.

2.4.2 Models of Disturbances to the System

2.4.2.1 Disturbance Analysis and Classification

When system energy loads, supplies and distributions are constant over any length of period, then the conditions for optimal energy usage also remain constant over the period. Hence the longer these constant periods, the fewer optimal solutions that have to be found. Ideally, this constancy is permanent, thus the optimal conditions are static: for a practical system however, the arrival of disturbances of various types disrupt the optimal set-up at various intervals.

It can be seen that the nature, arrival time and length of these disturbances are critical to the design and operation of any optimizing system. Consequently, study of the various types of disturbance with regard to the system model is required.

The various perturbations the system may undergo are of the following approximate types:

1. Planned shutdown of basic sections of the plant, e.g. for planned maintenance, or where plant is not worked 24 hours per day.

2. Unplanned shutdown of basic sections of plant. This is principally due to failure or potential failure of some element in a series operation. Maintenance would normally follow such a shutdown. Notice that at some stage in this maintenance, an accurate prediction of downtime would be possible, hence this type would merge with Type 1.

3. Planned load change e.g. when it is known that a following or preceeding unit in the system is going to either shut down, or change its input requirements.

4. Unplanned load changes. e.g. changes in production due to environmental conditions or developing failures. If the latter, then this type may lead to types 1 and 2.

5. Composite load changes. This loading type is the result of aggregation of minor loads. The total load varies in some fashion about a mean value. Note that the average value may vary as types 1 or 2.

The above "plant-orientated" disturbances may be classified into two broad groups:

A. Deterministic i.e. Disturbance occurrence time and length known in advance.

Planned shutdown, planned load changes, and some composite load average values may be included. These may be grouped:

(i) Overall management policy. This policy leads indirectly to certain deterministic information e.g. newsprint production, quality constraints.

(ii) Production cycles. This includes sections of the plant which do not work continuously (e.g. sawmill and wood preparation) and those process units involved in batch production (e.g. digesters).

(iii) Internal scheduling. This accounts for those process units not under direct control in the model, and is effectively section to section demand satisfaction e.g. if the chlorine plant has been shutdown on maintenance, production will be high on startup to bring storage up to suitable levels. Alternatively, as the sawmill has reserve capacity, if a large order is received, overtime may be worked (this affects (ii)).

(iv) Maintenance. When maintenance is known to be required, it is normally planned in some detail to ensure shortest downtime with regard to the importance of the process unit, and the availability of labour and machinery. Shutdown and startup times are thus known reasonably accurately in advance.

The information directly or indirectly obtainable from these four factors is generally of the same nature. Consequently, no further distinction will be made between the sub-types.

B. Probabilistic. Disturbance arrival time and length may only be expressed as a probability function. Unplanned shutdowns, load changes, and composite load instantaneous values may be included.

The behaviour of all demand consumers of the system model can be described by non-stationary probability distributions, where the time variation may be either deterministic or probabilistic in nature. Unfortunately, sufficient plant information and process knowledge is not available to either set up the stochastic process models (random walk, Markovian, etc.) to derive these distributions, or to construct the distribution empirically.

Consideration of the model shows that there are two types of consumer:

(a) Aggregated demands of process units (i.e. mill base loads). Components of the total may be considered uncorrelated, as the process units (in series with intervening storage, or in parallel) are relatively independent. Each process unit component of the mill base load is also made up of many small loads, and in general unless the process unit is completely shutdown, many of load increments will also be relatively independent. The degree of correlation between these incremental loads depends on the nature of the process.

For this type of consumer the true non-stationary distribution may be approximated by a stationary distribution. The average value and standard deviation of this stationary distribution may be regarded as constant, or can be varied in some manner depending on the throughput of the various contributing process units, the latter action reducing the loss of time information. In view of the approximation, and as an accurate stochastic production (and thus demand) model would also require a non-stationary distribution, only deterministic changes in the average values of the stationary distributions were made.

(ii) Individual machine, or directly connected serial process demands (i.e. paper machine loads). Maximum production of the total process depends on the state of each serial unit. Where the period of interest is well in excess of the mean time between individual unit variation, the production (and thus energy demand) may be approximated by an aggregated stationary distribution as above. When the production over a smaller period of interest is required however, this concept becomes inadequate due to the frequent failure situations. The true non-stationary distribution may then be approximated by three distributions, a stationary distribution to describe the normal operational throughput of the process, and related time-to failure, and length of failure distributions with time to determine whether or not a unit of the process (and thus the whole process) is in a failure state (i.e. zero production). Once failure has occurred, examination of the plant by experienced personnel may enable the length-of-failure to be deterministically fixed.

There are two types of failure distribution:

(a) Non random. Where time-to-failure or failure lengths are not random in occurrence. Individual consideration of components of the system (e.g. paper machine wire) result in non-random, correlated time to failure and failure length distributions. Some failure length distributions (e.g. paper machine dry end downtime) are also non-random although the time to failure distributions may be random.

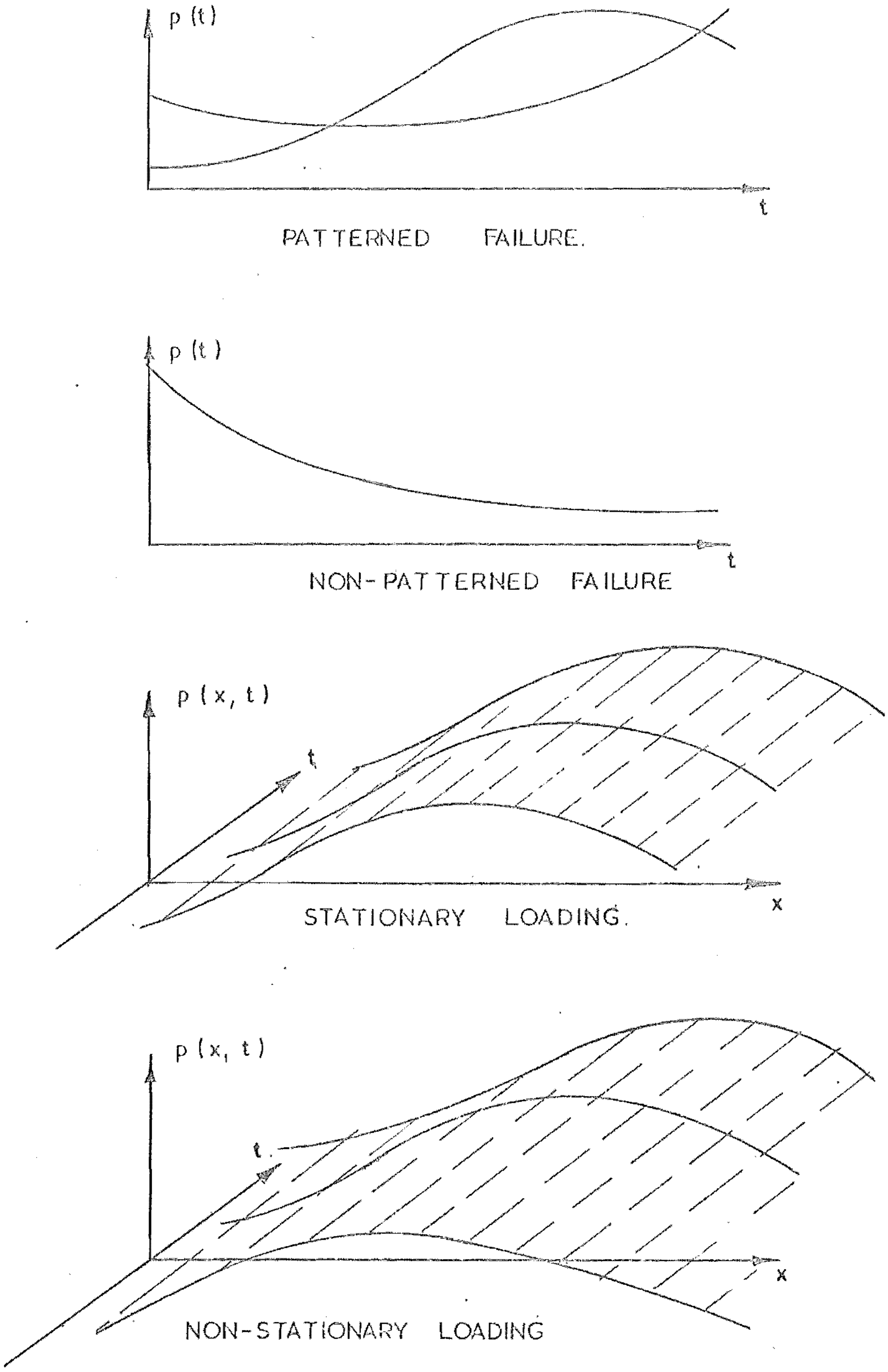


FIG 2·21 EXAMPLES OF DISTRIBUTIONS APPLYING TO VARIOUS PROBABILISTIC DISTURBANCES.

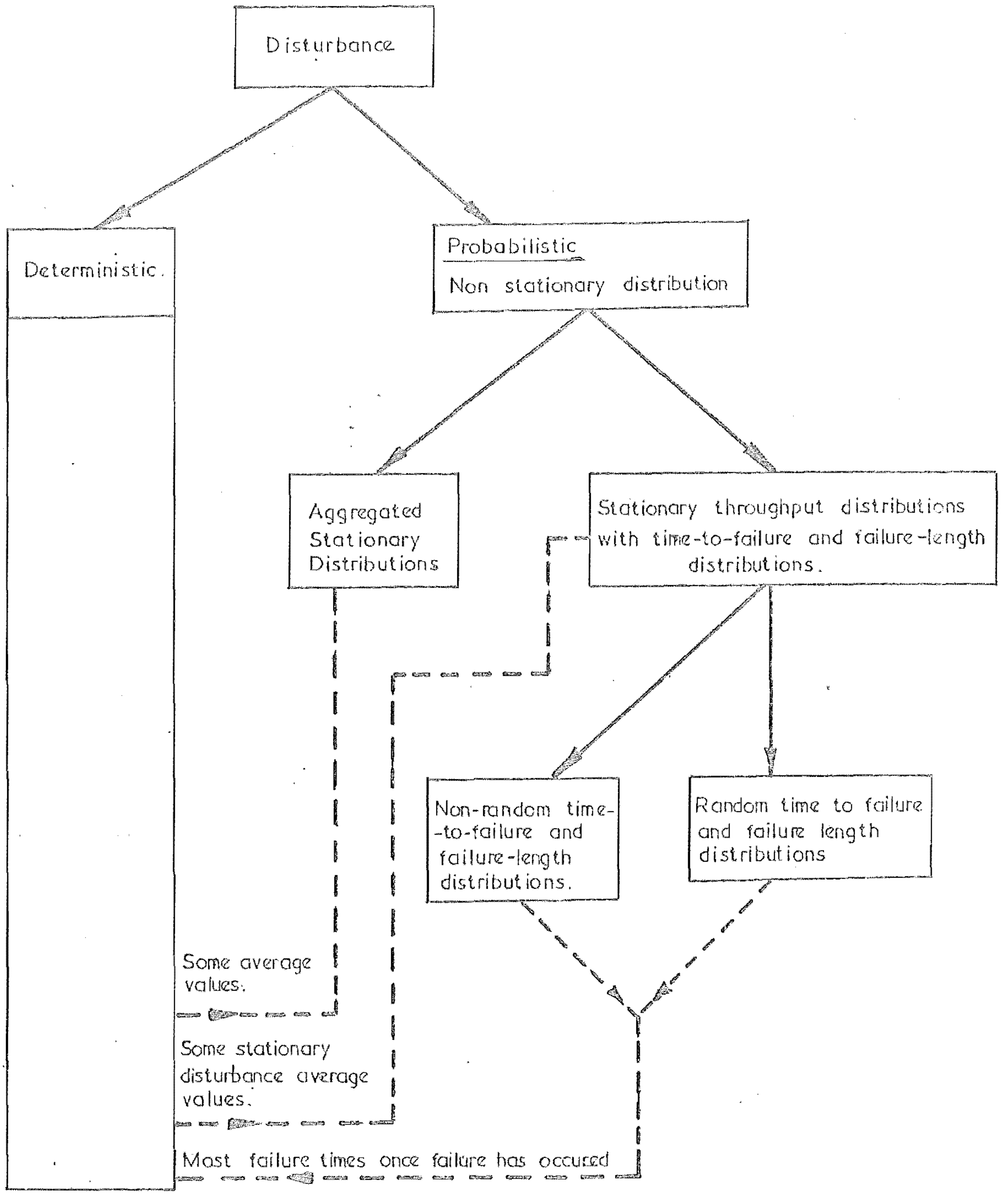


FIG. 2·22 DISTURBANCE ANALYSIS & CLASSIFICATION.

(b) Random. Where the disturbances occur randomly with time, i.e. the probability distributions are exponential. Often the result when many components of a system are considered en masse for time-to-failure, no particular component having a predominating effect, e.g. Paper machine dry end time-to-failure.

Illustrative sketches of the basic types of distribution may be found in Figure 2.21. The disturbance analysis and classification structure is featured in Figure 2.22.

2.4.2.2 Models of the Disturbances

Construction of accurate deterministic and probabilistic disturbance models for future system behaviour prediction and sensitivity studies is not possible without direct observation of the system. This is because the data available does not completely describe the system and its interactions, has generally a one day sampling interval (a much higher sampling frequency is necessary), and is often contradictory.

With regard to the system model of Figure 2.16, the loadings and time dependent transfer coefficients of prime importance have been considered, resulting in nominal disturbance or loading models.

(i) Paper Machine

Four related nominal models have been constructed for these key process units:

(a) Aggregate daily production

Stationary distributions for the two machines were plotted as histograms using the data of Period 9, 1968. Smooth distributions which approximately fitted these distributions were obtained by computer simulation and visual comparison:

$$P(y_i) = b_i \left[\lambda_i e^{-\lambda_i y_i} + \frac{a_i}{\sigma_i y_i \sqrt{2\pi}} e^{-\frac{1}{2}\left\{\frac{\log_e y_i - \mu_i}{\sigma_i}\right\}^2} \right]$$

where y_1 = No. 1 paper machine daily production normalized over range 0-310 tons day;

$b_1 = 0.025$, $a_1 = 50$, $\lambda_1 = 0.002$, $\mu_1 = 0.5$, $\sigma_1 = 1.0$

y_2 = No. 2 paper machine daily production normalized over range 0-390 tons/day;

$b_2 = 0.025$, $a_2 = 50$, $\lambda_2 = 0.002$, $\mu_2 = 0.3$, $\sigma_2 = 1.0$

(b) Aggregate lost time/day

The stationary distributions were plotted for the period 1 November 1965 to 31 October 1966, and are shown in Graphs 2.1 and 2.2. Three curves are shown for each machine:

(i) time lost on paper machine - rest of mill operating

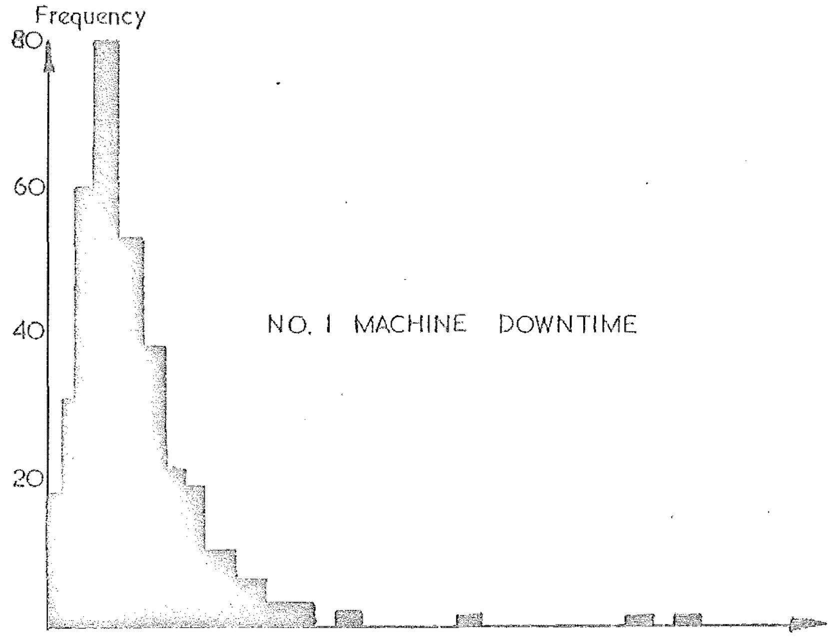
(ii) time lost where mill shut down

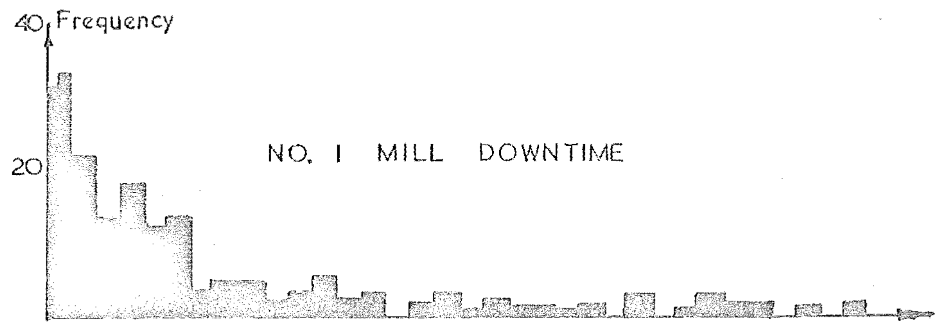
(iii) total time lost

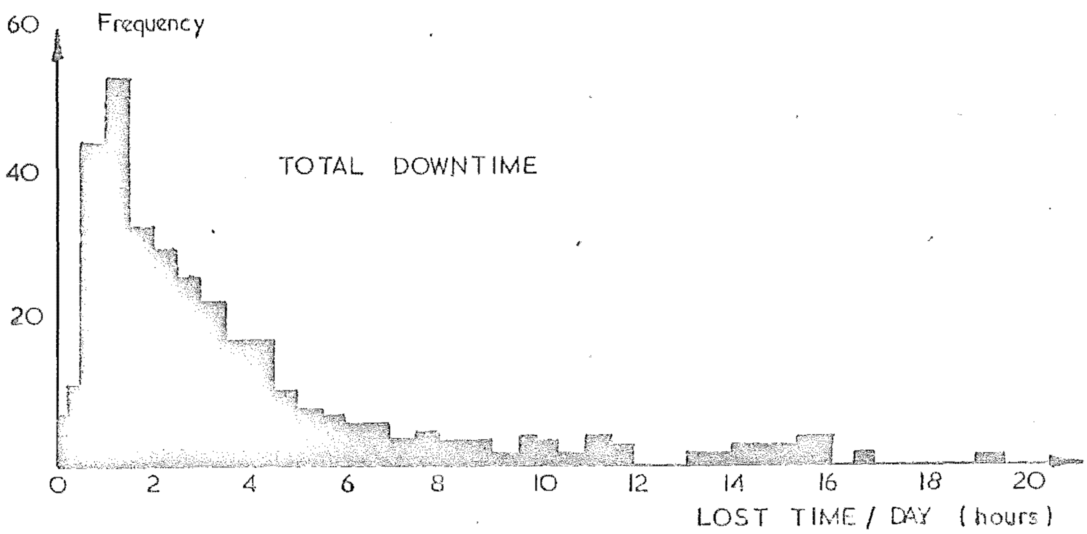
If lost time/day = Z, then the daily production is given by (24 - Z) * Production rate. As production rate is normally at a maximum it can be assumed constant, or may be given by a stationary distribution.

(c) Failure modelling

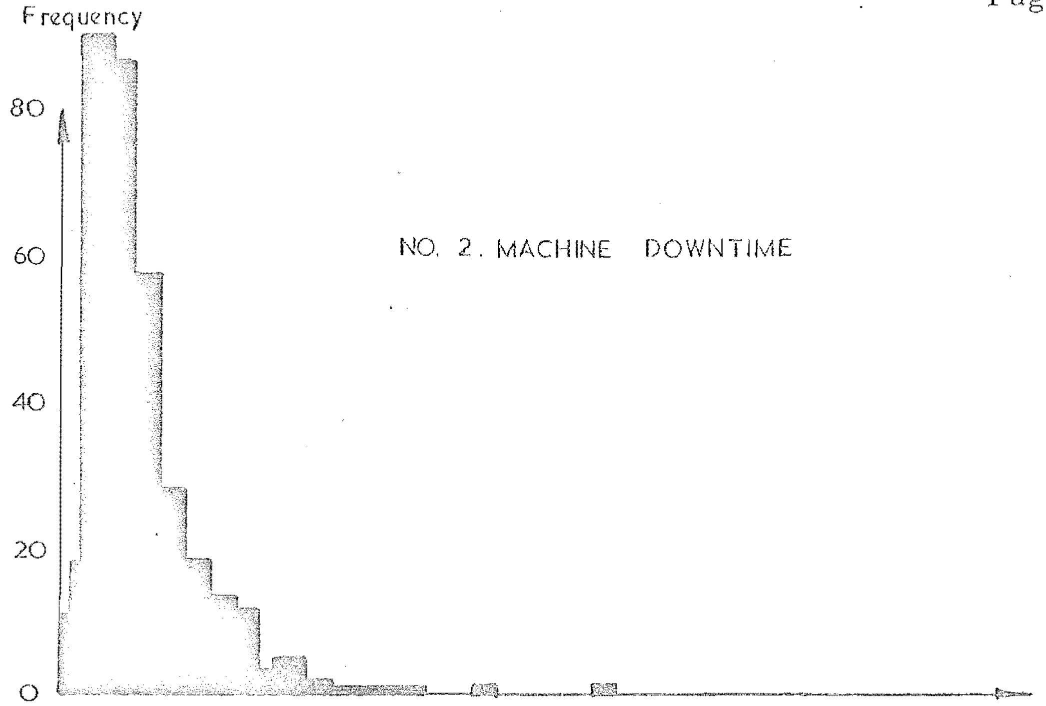
This model of paper machine behaviour gives a short term representation of finished paper and broke productions. A composite machine is divided into its three main sections as shown in Figure 2.23; time-to-failure, and failure length distributions being determined for each section. For normal operation, dry end and reel failures are generally of short duration and preceding sections are not shut down. Hence, during a dry end or reel failure, broke is produced in large quantities. A wet end failure does not produce broke, and very often results in machine shutdown.

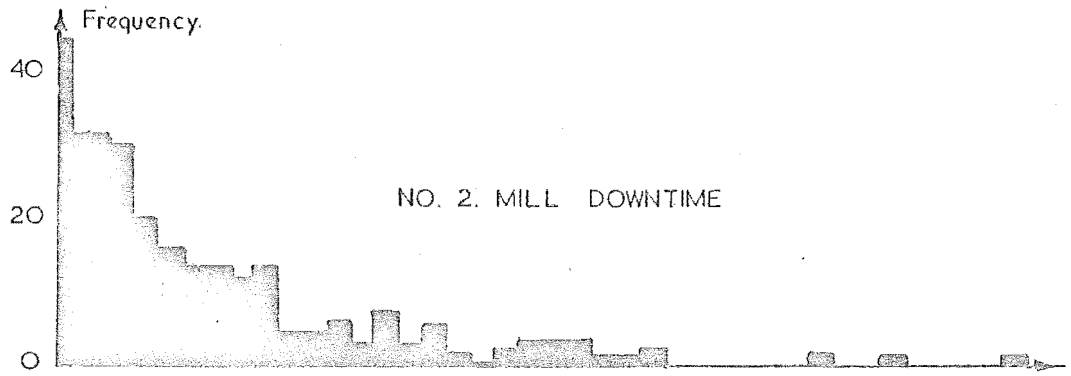


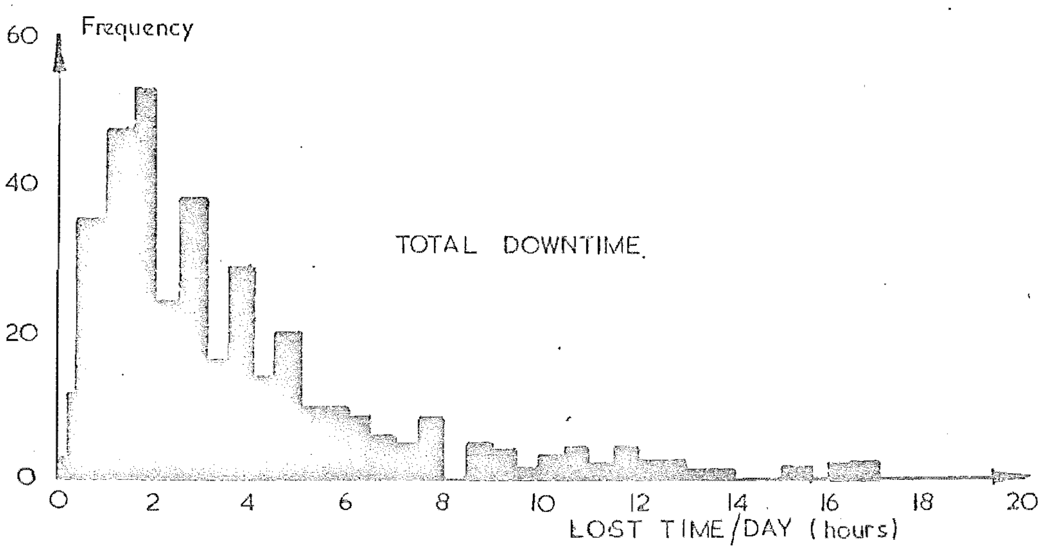




GRAPH 2·1 NO. 1 PAPER MACHINE LOST TIME DAY PROBABILITY DISTRIBUTIONS







GRAPH 2·2 NO. 2. PAPER MACHINE LOST TIME/DAY PROBABILITY DISTRIBUTIONS

A certain % of finished production is repulped mainly because of trim and quality considerations. This % has here been taken as constant at 9.6% although it could be regarded as a separate distribution.

The time-to-failure, and failure length distributions for each section of the machine were plotted using paper break information on No. 2 machine from November 1968 to March 1969. It was found that the time-to failure of all sections of the machine could be described by exponential distributions as follows:

$$\text{Prob failure } (t) = 1 - e^{-t/T_i}$$

Where: T_i = Mean time to failure of section i
= 6 hours for wet end
= 40 hours for dry end
= 1.5 hours for reel.

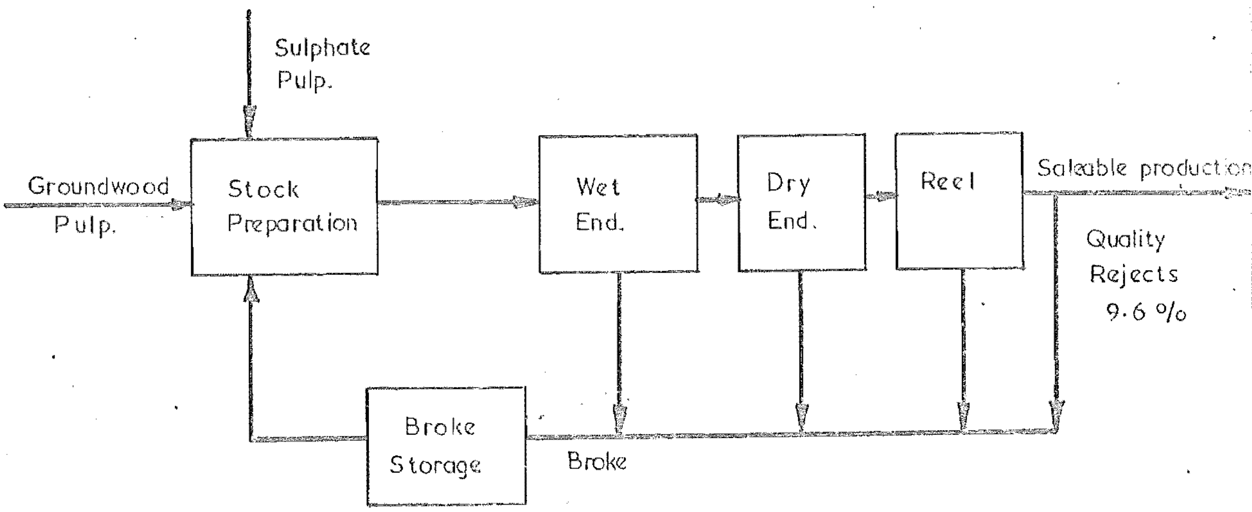


FIG. 2·23 THREE SECTION REPRESENTATION OF A PAPER MACHINE.

(d) Production rate

No information is available on machine production rates. Normal policy is to maintain production (i.e. machine speed) as high as possible, thus a distribution with small standard deviation could be expected. A nominal normal distribution has been assumed; this is given by:

$$P(r) = \frac{1}{\sigma\sqrt{2\pi}} \; e^{\frac{-\frac{1}{2}(r - u)^2}{\sigma^2}}$$

where r = maximum production rate (tons/hour)

u = 28 tons/hour

σ = 1.5 tons/hour

(ii) Mill Base Loads

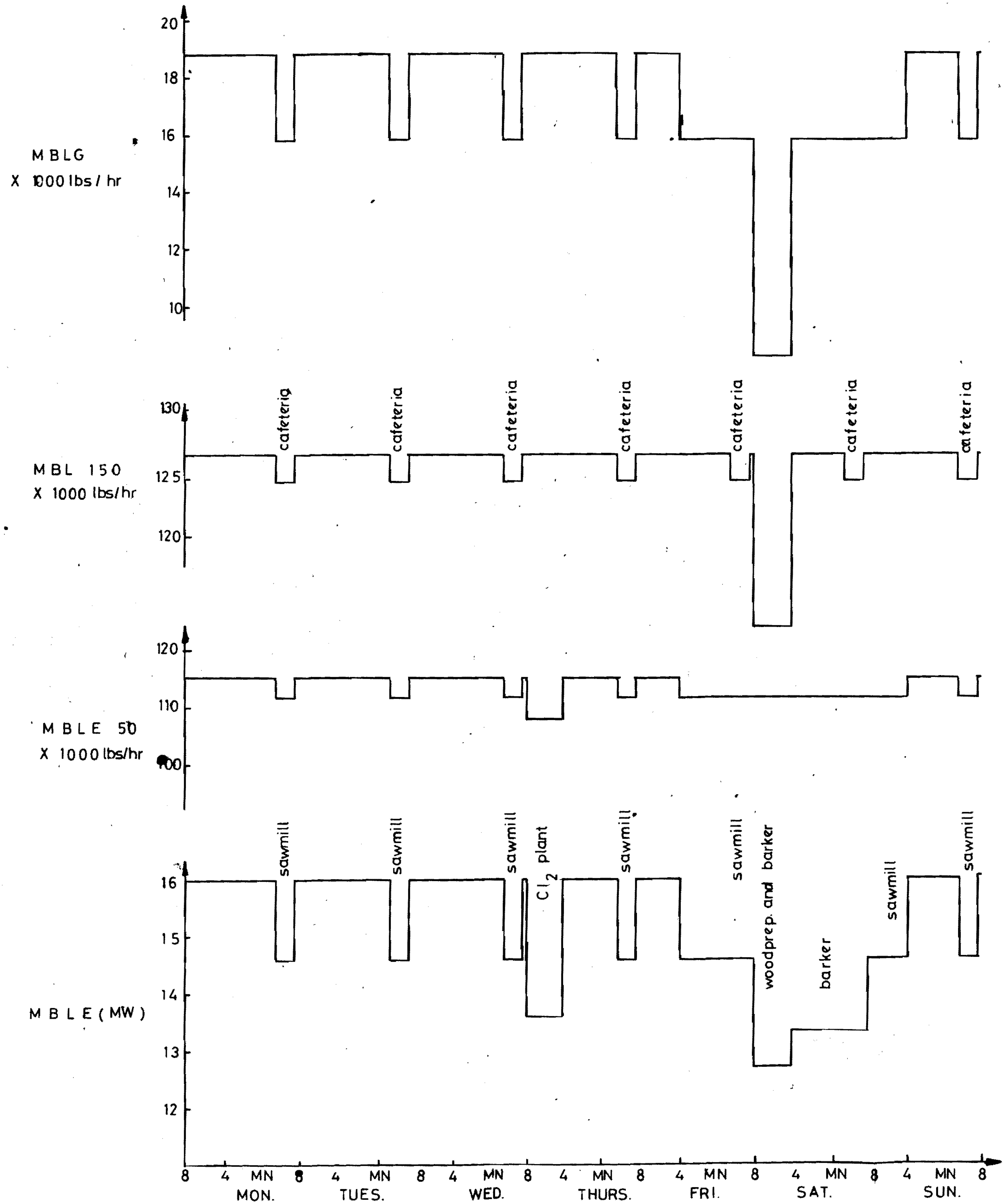
These loads have been modelled using a stationary distribution, with a deterministically varying average value. Using data from Period 9, 1968, histograms of daily load versus frequency were plotted. If the multiple individual loads which make up the process unit components of the mill base load can be assumed to be relatively uncorrelated, then by the Central Limit Theorem (36, 37), the mill base load distribution is normal. As the histograms appear normal, this distribution function has been used as a nominal model.

$$P(L) = \frac{1}{\sigma\sqrt{2\pi}} \; e^{\frac{-\frac{1}{2}(L - u)^2}{\sigma^2}}$$

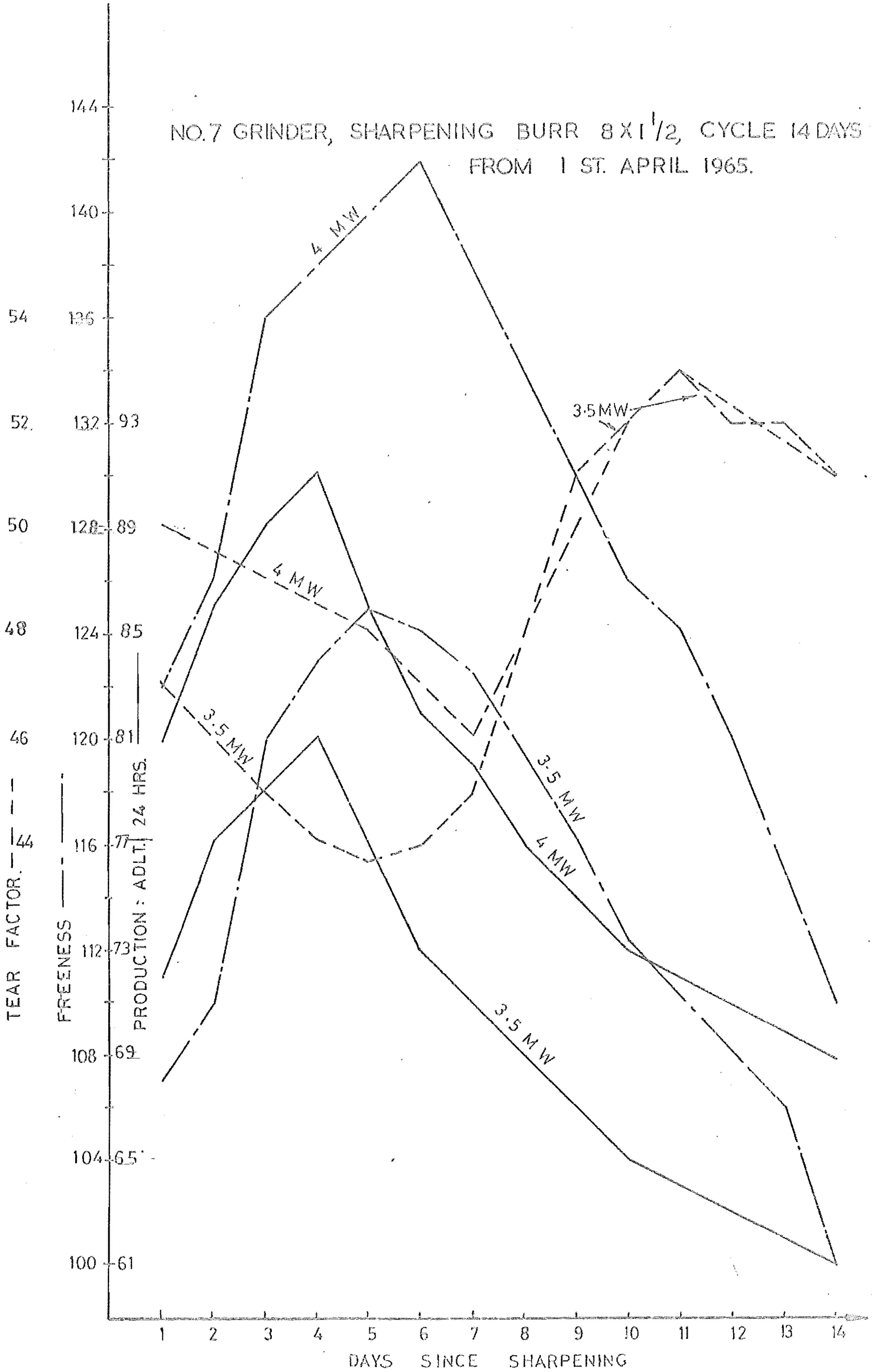
where L = total daily load (lbs/hour, KW)

u (MBLG) = 450,000, u(MBL650) = 2,250,000, u(MBL150) = 3,050,000, u(MBL50) = 2,750,000, u(MBLE) = 16,000, σ(MBLG) = 50,000, σ(MBL650) = 100,000, σ(MBL150) = 350,000, σ(MBL50) = 150,000, σ(MBLE) = 4,000.

The deterministic average value variation depends on maintenance and hoursof work etc, which may vary from week to week. The effects of a typical week of operation are shown in Graph 2.3.



GRAPH 2·3 DETERMINISTIC INFORMATION FOR A TYPICAL WEEK OF OPERATION — PAPER MACHINES NOT INCLUDED.



GRAPH 2·4 SHOWING THE RELATION BETWEEN GRINDER VARIABLES, TIME FROM SHARPENING, AND LOAD.

(iii) Grinder Total Efficiency

Grinder performance is not well understood, however a nominal approximation to the real process is possible with the aid of several simplifying assumptions. Each grinder characteristic is a function of; time-from-sharpening, load, and input timber quality. Graph 2.4 shows a typical relationship between horsepower days per ton (HPDPT) and the first two variables; it can be seen that the effect of load is relatively small. Neglecting this effect gives:

HPDPT = fn (time since sharpening, timber quality)

Assume that the time since sharpening, and sharpening decisions give rise to a relatively deterministic cyclic characteristic; and that variations in timber quality give rise to a randomly distributed variation about this characteristic. Grinder performance can thus be approximated by a stationary distribution having an average which varies as a deterministic cycle. The total grinder characteristic is the sum of individual grinder characteristics, dependent on load sharing arrangements. The deterministic cycles of individual machines can thus be considered as combining in a relatively optimal manner (by controlling the load to give a reasonably deterministic behaviour for the total). The corresponding stationary distribution describing variation about this deterministic mean can be considered as normal by the Central Limit Theorem (36, 37). A further assumption that the deterministic variations may be smoothed by the action of eleven grinders in parallel, and the effect of refiners and raffinators, allows grinder behaviour to be completely described by a stationary normal distribution.

A plot of total groundwood HPDPT versus frequency for Period 9, 1968 shows some relationship to a normal distribution. Unfortunately deterministic information was not readily available, so for test purposes grinder behaviour was nominally described by the normal distribution fitted to the available data:

$$P(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left\{\frac{y-u}{\sigma}\right\}^2}$$

Where: y = HPDPT; $u = 65$; $\sigma = 2.5$

2.4.3 A Model of Typical Operation of the System

To aid comparison of normal operation of the mill, and operation determined using optimizing systems, normal operational data for Period 9, 1968 was collected. This data is shown in Table 2.4. The values given are daily totals, as finer sampling intervals were not possible for all variables.

Table 2.4 Operational Data for Period 9, 1968

#1 P.M. Prod. (tons)	#2 P.M. Prod. (tons)	MBLE (KW)	MBL650 (000 lb/hr)	MBL150 (000 lb/hr)	MBL50 (000 lb/hr)	MBLE (000 lb/hr)	HPDPT
147.3	360.3	7924	-2197	2992	2733	539	68.3
274.1	356.2	14349	-2253	2773	2749	485	62.8
258.9	269.9	23488	-2231	3196	2890	488	61.6
195.0	348.3	14746	-2078	3194	2844	499	65.1
149.8	353.9	20264	-2218	3060	2775	412	61.5
269.2	237.1	16868	-2402	3076	2717	401	62.9
273.0	363.3	5817	-2116	2293	2355	566	66.1
282.8	384.5	11100	-1652	2275	2403	341	64.6
281.6	364.0	14021	-2276	3229	2585	427	65.1
287.3	354.5	15751	-2391	3439	2633	444	62.2
267.8	346.2	17058	-2367	3395	2612	441	66.8
266.9	364.0	15595	-2302	3351	2772	453	65.2
274.9	367.2	12046	-2362	3097	2689	435	62.4
181.8	306.0	22356	-2385	3298	2624	490	71.7
289.4	0.0	23148	-2266	3012	2547	423	46.0
261.8	0.0	6807	-2127	3113	2763	444	62.1
269.9	247.9	7161	-2369	3461	2569	460	65.7
276.8	316.5	9489	-2346	3379	2509	442	60.9
305.7	298.7	14451	-2267	3259	2836	329	55.8
153.6	366.6	16697	-2360	3250	2878	258	67.4
212.2	331.1	17203	-2315	3023	2784	485	68.7
234.5	188.8	24331	-2350	2837	2701	484	65.5
265.2	261.3	17316	-2229	2815	2742	426	63.7
185.9	358.6	17593	-2071	2940	2886	351	62.5
287.7	258.8	14307	-2221	2817	2868	457	72.7
232.1	382.8	13844	-2384	2689	3042	480	65.4
254.4	380.5	14376	-2412	2813	2779	458	68.6
245.9	366.0	14510	-2319	3111	2870	467	68.2
232.4	367.3	16961	-2384	2940	2859	485	63.1
250.9	329.4	15991	- 475	1833	2462	387	62.7
276.4	336.9	16912	-2043	2231	3028	516	66.4
265.0	364.4	16285	-2135	2860	2912	502	66.3
246.4	289.1	20336	-2326	3065	2989	440	68.8
226.5	329.9	19312	-2278	3243	3037	406	72.5
267.6	185.6	23360	-2256	2668	2701	467	68.1

2.5 SUMMARY

Each major section of this chapter has considered a different aspect of the total problem formulation.

The basic objectives of the study, and the interactions of these objectives with the overall objectives of the larger problem of optimal overall mill operation were considered in 2.1. 2.2.1 considered the wider system objectives from a macroscopic, or management viewpoint, yielding some general observations on the suitable features of the study. Section 2.2.2 identified the major operational problems of the wider system in hierarchical form, and utilised this to construct a decision making hierarchy for the wider system. This structure provides a framework for co-ordinating further research into control of the Tasman mill system.

Following from this basic structure, the energy optimisation problem was decomposed into a more detailed hierarchy. The specific problems at each level of this hierarchy were considered in detail, this giving basic specifications for the solution algorithms required.

Section 2.4 was concerned with modelling both the physical configuration of the system and the behaviour of major system components. There were three basic parts to this exercise. A model of the mill system relevant to the energy optimisation problem was developed in 2.4.1 by using an aggregation policy. This method yielded an hierarchical structure of models, the lower levels of the structure becoming more problem-specific. Analysis and classification of the various disturbances to the system was undertaken in 2.4.2, this leading to the construction of empirical probabilistic models of the behaviour of the major system components. Finally, data relating to a normal period of operation of the mill system was compiled in 2.4.3.

The following two chapters are devoted to the development of algorithms to solve the problems isolated in 2.3, using the physical and behavioural models of 2.4.

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CHAPTER 3 OPTIMUM CONTROL ALGORITHMS: SURVEY AND DEVELOPMENT OF EXISTING ALGORITHMS

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CHAPTER 3

INDEX OF ILLUSTRATIONS

CHAPTER 3 OPTIMUM CONTROL ALGORITHMS: SURVEY AND DEVELOPMENT OF EXISTING ALGORITHMS

3.1 INTRODUCTION

This chapter, and the following chapter, deal with the design of algorithms which solve the subproblems of the overall study described in Chapter 2. While Chapter 4 is concerned with the development of new algorithms to solve particularly difficult subproblems, this chapter describes the application and modification of existing methods. Unavoidably, there is some overlap between the two chapters as both have a similar function. Some of the subproblems, for example, the Static Long Term Optimisation, are completely dealt with in this chapter as an existing algorithm (Linear Programming) can be directly applied. In other cases, notably the Optimal Scheduling Problem, various existing methods have been considerably extended and modified (3.4.2.) without achieving the desired characteristics, - this problem is re-considered in Chapter 4 and solved by developing a new algorithm (Dynostat). In the case of the Sensitivity Analysis of Optimal Schedules, there is no existing method to solve the problem, and again a new algorithm is developed (4.3).

The major concern of this, and the following chapter, is the general subject of optimisation theory, particularly its application to process control. "Optimisation" has been the subject of considerable study, particularly over the past twenty years. There are now a large number of academically formalized techniques, many of which have been applied to solve a wide variety of existing problems. The extensive list of survey papers and textbooks at the conclusion of these chapters reduce the necessity for a major survey here. However, very few applications concerning the optimisation of consumer energy usage have been reported, most studies in this region dealing with optimal production of energy for transmission to consumers. A brief survey of relevant applications is given in 3.2, as well as those referenced in particular contexts throughout the two chapters.

As previously mentioned, process control algorithms for the short term control level are outside the scope of this study. Accordingly, algorithm development has been presented in terms of the remaining two basic problem levels - the upper long term planning level, and the intermediate optimal scheduling level.

Throughout the development of the subproblem solution methods, practical implementation has been a foremost consideration, manifesting itself in a preference for simplicity of concept, and low computational requirements in terms of computer time and storage. Methods having those advantages (usually those with more restricted application) thus receive first consideration, more complex methods (usually having greater generality) are studied later.

3.2 A SURVEY OF RELEVANT APPLIED ALGORITHMS

Applications of interest with respect to the algorithm design in this and the following chapter involve dynamic scheduling, sensitivity studies, optimal reordering and static optimisation.

Reported applications can be considered in three basic classes, with relevance as follows:

(i) Aeronautical and Space Activities

Two surveys of work in this region (1, 2) give a total of approximately 400 references. Much of this work involves the optimisation of dynamic system trajectories, which relates to the dynamic scheduling problem. Variational methods are commonly utilised. Although these techniques avoid the dimensionality problems of dynamic programming, they do not handle disturbances explicitly; a requirement of the scheduling problem. As a consequence, initial solution algorithms did not utilize these methods. Present study within the overall group project is concerned with modifying such variational methods to suit the allocation and scheduling problem. (J. F. Lowinger).

(ii) Chemical System Process Control

A number of surveys (3, 4, 5, 6, 7, 8, 9) give extensive coverage of the work in this field. Generally, optimisation is applied to specific processes to improve product quality; rarely is energy consumption considered as in this case. Two examples which have considered this aspect are (10, 11) however the techniques utilised employ selective load shedding, and a single, variable energy source. Such techniques would be extremely limited in this energy optimization scheme. A scheduling application which is more similar to the energy optimization problem (12), uses a simulation approach, where schedules are selected by some means, simulated on a fast-time process model, and compared on a performance basis. The strategy utilized for the example given is a form of heuristic search algorithm, which is not considered applicable to the Tasman system owing to the relatively large number of variables involved.

A number of examples of optimal reordering applications are given in (13, 14). While sensitivity studies using the linear programming method (15), and to a lesser extent using static non-linear programming methods (16, 17) appear to be relatively well formulised it would seem that sensitivity of optimal trajectories has not received a great deal of attention in process control.

(iii) Electric Power Supply Industry

Many surveys of on-line and off-line optimisation and computer control applications in this field are available (18, 19, 20, 21). Of the optimisation applications studied, the scheduling of hydro-steam systems for minimum cost (with respect to the load requirement), offers closest correspondence with the energy scheduling problem. In a sense the hydro system problem and the energy optimisation problem can be considered to have a direct relationship. The hydro system model has a stochastic storage input, storage output being controlled to meet system loads (22); whereas the Tasman system can be considered as having controlled input to storage, and stochastic storage output load demands. Both problems involve storage dynamics and demand satisfaction, although the energy optimisation problem involves multiple demands (compared to the single loading demand of a generating system). (61, 63).

This close correspondence between the two problems has resulted in a useful carryover of concepts, especially in the initial stages; although later work has tended to diverge from the hydro steam techniques to enable greater utilisation of the particular features of the Tasman system. Particular references consulted will not be listed at this point, but are acknowledged in the text.

3.3 DEVELOPMENT OF EXISTING ALGORITHMS FOR THE LONG TERM PROBLEMS

The specification and elucidation of the problem at this upper level of the control hierarchy has been considered at some length in Chapter 2.3. Figures 2.8 and 2.12 show the decomposed subproblems relevant to this study, in the form of an algorithmic solution policy.

The problem decomposition which has been derived is considered to yield the simplest and most economic solution algorithms for the particular problem specification. It is however, by no means unique. For the similar problem of multipurpose reservoir design, other authors have produced different approaches. Young and Puentes (32) use a simulation approach where the integral of the difference between water inflow and demand is plotted against time. The resultant curve is cyclic the maximum difference between each peak and the following troughs defines the storage required with time. Little information is given on what data should be used in the analysis; the example given uses artificial data typical of a yearly wet-dry cycle. Apart from this apparent inadequacy, the method makes no allowance for operating policies, or for variations in inflow and demand from those expected.

A similar approach is given by Hall et al (57). Here, simulation is used to determine the critical period, i. e., the interval between the conditions of maximum and minimum storage level, for various storage capacities and operating policies. System demands and losses are assumed, and historical hydrologic records are used to evaluate various combinations. A Monte Carlo approach to provide synthetic stream flow sequences is also proposed. A major shortcoming of the study from a design point of view is that no systematic method of improving the situation is put forward for the case where operating policies are more complex than those assumed.

Hall (58) bases a more sophisticated method on the concept that the economic return in each time period is only a function of water release. For a certain reservoir size the optimum operation policy, and therefore maximum return, was calculated by using a dynamic programming technique (39). This technique was used for several reservoir sizes, and the size which produced the highest net benefit was selected as the best design. The disadvantage of this method is the computational requirement, especially if probabilistic variations are to be accounted for.

A very similar method is used by Mobasheri and Harboe (54) to formulate a two stage optimisation system for a single reservoir. The two stages are: 1) computation of the optimum operation to maximise economic return for a feasible design, and 2) selection of the best design based on information obtained from the first stage. The synthesized model uses a dynamic programming technique to determine the optimum operation, and a systematic sampling method to select the optimum design, from designs for which optimum operational rules are determined. The data used in computation is a fifty year streamflow record over the critical period, the reservoir minimum size is based on worst case design. In addition the authors give a brief resumè of other work in the field, adding that the possibilities of combining simulation and mathematical programming to formulate an optimisation system for the design function has not received adequate attention.

A computational scheme similar to that of Mobasheri and Harboe, except using the Dynostat (see Section 4.2) algorithm for the first stage, was considered. However, the non-stationary nature of the system, and the extremely large computational requirement, especially when sensitivity analyses are added, mitigate against such a formulation. Consequently, the combined simulation - mathematical programming approach was investigated as discussed in Section 2.3, thus resulting in the algorithmic solution policy of Figure 2.8.

3.3.1 Static Long Term Optimisation

Little work has been performed here as this aspect was studied in a concurrent investigation at Tasman by B. Hoult. As a linear model was assumed, the I.C.L. "Linear Programming Mark 2" package was used to perform the operation. Details of the model, assumptions, and results are given in a Tasman report dated 3 December, 1968. The report concludes that in the static long term sense the energy system is presently operated in an optimal manner.

The linear programming "package" developed during the course of this thesis could be used directly in this function. Alternatively, studies of the system may indicate that optimisation using a non-linear method is more valid. At the present time, information on the system components to permit such a judgement is not available. Intensive experimentation is required to determine component characteristics.

Little difficulty is foreseen should such an investigation show that a non-linear method is more warranted. The multitude of non-linear optimisation techniques available (16) ensure that the main problem will be one of selection.

3.3.2. Steady State Sensitivity Analysis

This aspect was also covered for the case of a linear model. The linear programming package used, outputs both the primal and dual solutions to the optimisation problem: the dual solution gives the marginal costs of the various variables, the range of values of the constraints and loadings for which the solution remains possible, and identifies the variables which leave the solution if these values are exceeded. Results of the Tasman work show that the optimum solution obtained is very stable, the minimum increase in cost required to change the basis from optimality to non-optimality being of the order of 100%.

In addition to optimisation for normal conditions, an additional five optimisations were performed with various major energy supply or conversion units out of commission. Satisfactory basis solutions were obtained in all cases, the maximum cost increase being 30%.

If future investigation should show that a non-linear optimisation method was warranted, sensitivity information on the optimal solution could readily be obtained by use of the perturbation techniques as outlined in Section 4.3.

3.3.3. Analysis of the Dynamic Characteristics of the Optimal Solution

As discussed in Section 2.3 every solution to the static long term optimisation above, has associated dynamic characteristics. These determine the ability of the system to meet operational peak demands: analysis is therefore required to give a total picture of the proposed solution. An example of a variable whose optimum value is determined by the static optimisation is "available groundwood storage". Variation of this value directly affects the slow response dynamics of the system.

The technique evolved is a simple adaption of the Monte Carlo constraint sensitivity analysis of 4.3.1.; the Monte Carlo analysis being applied directly to a consistent nominal trajectory (taken as constant storage at the mean level to reduce bias effects). Thus for any proposed plant and energy allocation, average loading and efficiency distributions obtained from previous operation can provide information on the system constraint sensitivity (60).

In addition, the effects of parameter variation can be readily assessed. Analysis of the variation of a particular major system parameter (NZED maximum demand) has been carried out in development work. The results, conclusions, and suggestions for improvement are given in (64).

The distributions used in this work are as discussed in 2.4.2.2. and are briefly described in Table 3.1. The plant configuration used is as in "Period 9, 1968". Results of the analysis are summarised in a graph of "probability of lost production" versus "maximum demand value" (Graph 3.1). An interesting feature of this curve is the sharp cut-off, this indicating a relatively well defined optimum maximum demand value.

Table 3. 1 Disturbance Models

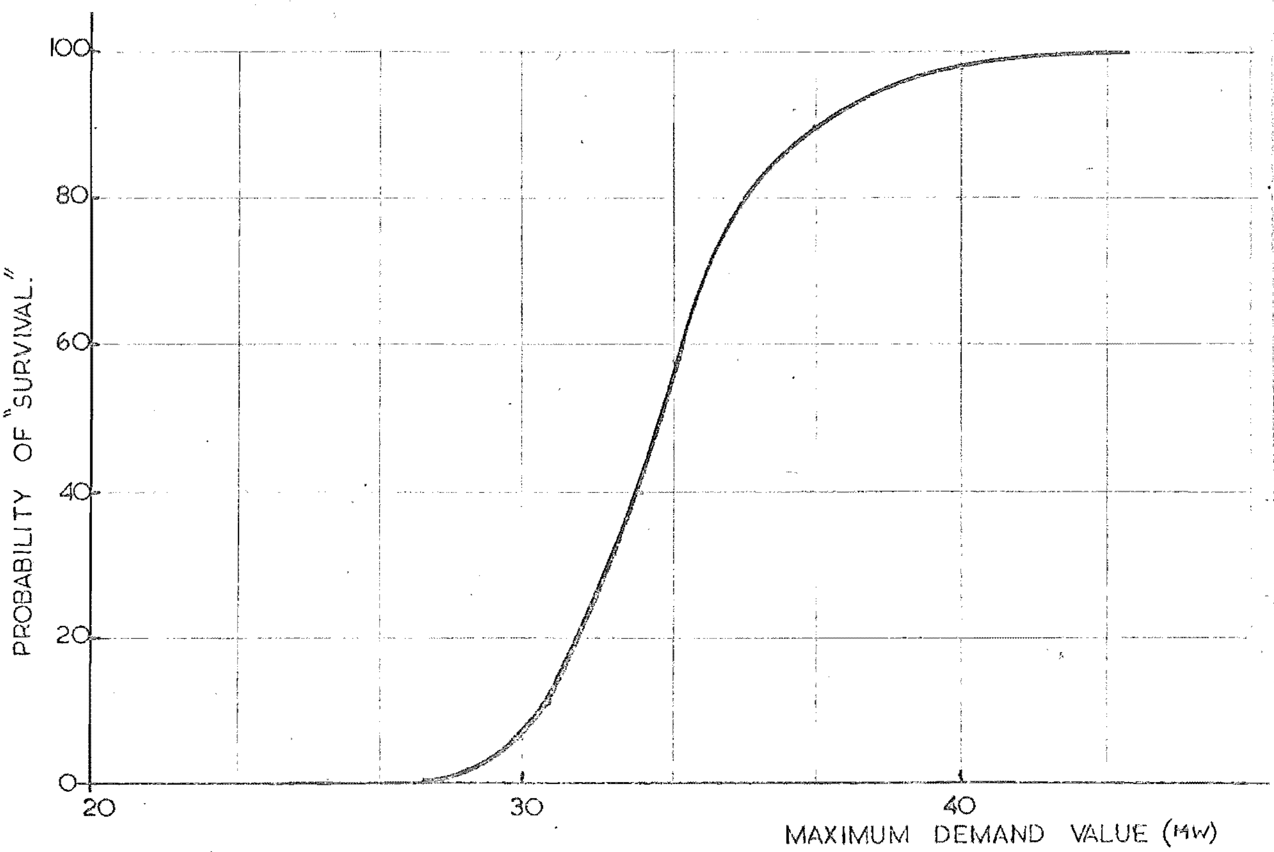
Variable	Distribution Assumed	Reason
MBL's and HPDPT	Normal	Each value can be thought of as the mean of a sample from a large population. Sample mean distribution tends to normal by the Central Limit Theorem.
Time-to-failure. P. M. wet end, dry end and reel	Negative Exponential	This curve results from failures occurring randomly with time. Appears to fit available data.
Length-of-failure. As above.	Combination Negative exp. and Log Normal	Appears to fit available data

Results given are relatively approximate due to:

1. Insufficient sample lengths for accurate demand and unit efficiency distributions.
2. Insufficiently fine time discrimination in the analysis - this was limited to daily intervals by the form of available data; hourly intervals would be more suitable.

Simple extensions to the present simulation would permit the following:

1. Determination of the probable length of paper machine shutdown - this giving a cost figure, which, in conjunction with the probability of failure, would allow quantitative analysis of the desirable M. D. value directly from comparison with the M. D. cost.



GRAPH 3·1

PROBABILITY OF LOST PRODUCTION Vs M.D. VALUE.

2. Determination of the energy savings which could be obtained by increasing the groundwood storage by some given amount (for a constant probability of lost production and a given storage policy).

   Increasing available storage would permit the reduction of some other system parameter. The effects of storage are not considered directly in the steady state optimisation.

3.3.4. A Summary of the Algorithms for the Long Term Problems

In Chapter 2.3, the total energy optimisation problem was decomposed into an hierarchical structure of related subproblems, and an algorithmic solution policy for the long term level of this structure was derived as shown in Figure 2.8.

The preceding sections (3.3.1 to 3.3.3.) have presented the development of existing algorithms to solve the subproblems of Figure 2.8. For the static long term optimisation and the steady state sensitivity analysis, no development was required as this work was carried out in a concurrent investigation at the firm. A linear model was assumed, this predisposing a direct solution by linear programming. More information is required to prove or disprove the validity of this assumption but even in the latter case, it is confidently expected that standard non-linear static optimisation and sensitivity analysis techniques can be directly utilized. For the analysis of the dynamic characteristics of the optimal solution produced by the above two algorithms however, considerable development was required to produce an algorithm which fulfilled the requirements. This resulting algorithm is basically a modified Monte Carlo method, the particular configuration used in this application being a new development in the field. Suggestions for possible simple extensions to the power of the method were also presented.

3.4 DEVELOPMENT OF EXISTING ALGORITHMS FOR THE INTERMEDIATE TERM PROBLEMS

The specification and elucidation of the control problems at this level of the hierarchical problem structure has been considered in Chapter 2.3, resulting in a diagramatic specification of the algorithms required to solve these problems (Figure 2.12). This section of the thesis presents the attempts made to develop existing algorithms to meet these specifications. Section 3.4.1. presents an off-line low frequency algorithm to solve the optimal reordering problem, while Sections 3.4.1. and 3.4.2. present attempts to utilize existing static and dynamic optimisation methods to solve the optimal scheduling problem.

3.4.1. The Optimal Reordering Problem

A solution to the optimal reordering problem involves determination of optimal reorder levels, and reorder volumes for each commodity purchased from without the mill system. As the mill system under consideration has been in operation for a considerable time, this exercise has been performed, albeit empirically, generally in negotiations with suppliers. However, a periodic review using quantitative methods could be a valuable exercise, especially with changing economic conditions.

Without a detailed knowledge of the market place and of the firm's requirements, and without the ability to negotiate meaningfully with suppliers, little practical work can be done in this region. Algorithmic proposals however, can be put forward.

An outline formulation of a proposed inventory control system is given below. Alternative control techniques are treated extensively in the literature (14, 53, 55, 56).

Derivation of decision functions for the two parts of the problem (i.e. provision of operational storage; and provision of contingency, or reserve storage) are presented separately in 3.4.1.1. and 3.4.1.2. Independent decisions may be made, however for overall minimum cost a decision based on the combined decision functions as in 3.4.1.3. is preferred.

3.4.1.1. Provision of Operational Storage

Operational storage is the storage volume normally in use, in comparison with the contingency or reserve storage. When the operational storage level falls to zero, reordering is performed. The choice of the amount of operational storage to be provided is a simple optimization problem, where it is desired to minimise operating costs, i.e. to provide the minimum cost of stored material. Costs involved are the purchase cost of material, transport costs, and storage costs. The latter depend on financing arrangements for the storage volume, and on the type of product, e.g. whether a tank is necessary, whether agitation is required etc.

In general, purchase costs are dependent on the size of order, and may often be minimized by negotiation for a single source of supply. Such negotiation yields a curve of cost versus reorder size.

Investigation will simply reveal the cheapest form of transportation. Note that for each additional vehicle utilization, the curve of transport cost versus order size will show a step increase.

Given the average utilization of the stored product, the average number of reorders per year may be readily determined, hence the above curves can be converted to annual cost curves.

Storage volume must be sufficient to contain the order on arrival (unless distributed deliveries can be negotiated), hence storage costs are a direct function of reorder size.

Plotting the sum of the three cost functions against reorder size permits selection of the reorder size yielding minimum operational cost. This sum is the operational decision function. Determination of this decision function in practice depends markedly on purchase and delivery terms which can be arranged.

3.4.1.2. Provision of Contingency or Reserve Storage

This storage volume is determined by some acceptable low probability of being unable to supply system requirements. This reserve accounts for the lag between order and delivery and allows for industrial dispute in the delivery or supply industries.

From design data, or from compiled operational information, a distribution p(y) describing daily consumption, y, of the stored material will be available. Little or no information will be available on the serial correlation of daily requirements, assume then that these are independent.

Given that the contingency storage level when reordering is performed is set at level S, it is possible to compute the probability of exhausting stocks in i days:

viz: p(stocks exhausted in i days) =

$$p(y_1 + y_2 + y_3 + \dots\dots y_i > S)$$

$$= \int_o^S \int_o^{S - y_1} \dots\dots \int_o^{S - y_1 - \dots\dots - y_{i-1}} p(y_1)\ p(y_2) \dots\dots$$

$$p(y_i)\ dy_i\ dy_{i-1} \dots\dots d_{y1} \qquad \dots\dots \qquad 3.01$$

where y_j = demand on storage in day j.

In cases where this calculation becomes complex or where analytic distributions are not available, a Monte Carlo simulation can provide a rapid solution. (52).

Let the probability that goods ordered will be delivered x days following placement of the order be given as p (x). This distribution will most probably be a gamma distribution - see Page 88, (53). The probability that the goods ordered will not have arrived by day i is given by:

$$p(\text{non arrival by day } i) = 1 - p(x < i)$$

$$= 1 - \int_o^i p(x)\ dx \dots\dots \qquad 3.02$$

The overall probability of an outage of stored goods by day i, necessitating shutdown of some sections of the plant is thus:

p(outage by day i) = p(nonarrival by day i)* p(stocks exhausted in i days)

$$= \left[1 - \int_o^i p(x)dx\right] \int_o^S \int_o^{S-y_1} \dots \int_o^{S-y_1 - \dots\dots - y_{i-1}} p(y_1)p(y_2)\dots\dots$$

$$p(y_i)\ dy_i \dots\dots dy_1 \qquad \dots\dots \qquad 3.03$$

For any given level of storage then the probability of outage can be plotted against time. Although determination of this function by analytic means is possible, it would seem more economic to utilise the simple Monte Carlo simulation procedure. The "hazard rate" is the derivative of this function.

Note that as the probability is of a cumulative form, after a certain period of time, the curve levels off. This "practical maximum" value only is of interest, as it gives the effective probability that outage will ever occur, i.e. p(outage). This probability may be plotted for various values of S as before. The annual cost of the provision of contingency storage is a deterministic function of S determined by capital financing and type of material. A graph of storage cost versus probability of outage follows directly.

From the size of operational storage, the average number of reorders per year may be determined. Given the average cost per outage, the expected annual outage cost is:

Expected annual outage cost = (no. reorders/year) * (average outage cost) * (prob. of outage) 3.04

The total expected cost for some probability of outage is the sum of the expected annual outage cost and the annual storage cost. Plotting the total expected cost against the probability of outage allows the minimum total expected cost and associated acceptable probability of outage to be determined, hence the acceptable contingency storage.

3.4.1.3. Overall Cost Minimisation

The total expected storage cost is the sum of the operational cost and the expected contingency cost. The reorder size, which directly influences operational cost, is also a factor in the determination of the minimum budgeted contingency cost.

A procedure to eliminate this cross coupling in the selection of minimum total storage cost is as follows:

(1) determine the minimum expected cost for each allowed value of reorder size using the method outlined in 3.4.1.2.

(2) plot the sum of this value and the operational cost

(from 3.4.1.1.) against reorder size.

The overall optimum reorder size (i.e. operational storage value) can now be determined directly from this graph, and this value used to determine the optimum value of contingency storage by stepping back through the procedure of 3.4.1.2.

The total storage required is of course, the sum of the operational storage and the contingency storage.

3.4.2. The Optimal Scheduling Problem - Extended Static Methods

As discussed in Chapter 2, the problem here is to schedule intermediate production and energy distribution with respect to system loadings so as to achieve minimal operational costs. The optimisation algorithm(s) is required to treat storage explicitly (i.e. the dynamics of the system must be accounted for) and must have an on-line capability. In view of the design philosophy of proceeding from simple, fast algorithms to the more sophisticated routines, initial study concentrated on the extension of static methods to give a dynamic capability. Later work involved the more conventional dynamic methods (3.4.3. and 4.2). The model utilized for these studies is that given in 2.4.1.4. This model (Figure 2.16) is reproduced in Figure 3.1.

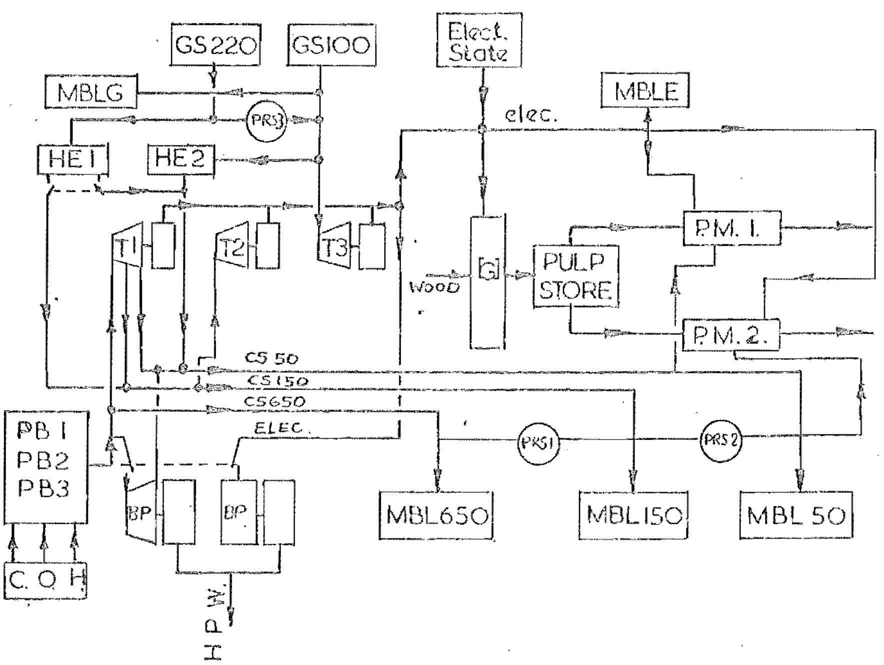


FIG. 3.1. ENERGY OPTIMISATION MODEL

Consider the application of ordinary static methods to the problem. Let the smallest interval of interest be t, and let the time horizon extend over N intervals.

As the system model and constraints are linear, the linear programming method can be used. Each interval problem can thus be formulated:

$$\text{Min. } F = c_1 v_1 + c_2 v_7 + c_3 v_8 + c_4 v_6 + c_5 u_{10} \quad \ldots\ldots\ldots\ldots \quad 3.05$$

$$\text{subject to: } f_j(\underline{y}, \underline{u}, \underline{v}) = O \quad j = 2, \ldots\ldots\ldots, 10 \quad \ldots \quad 3.06$$

$$\text{Min} \leqslant \underline{u} \leqslant \text{Max}$$
$$\text{Min} \leqslant \underline{v} \leqslant \text{Max}$$

where the notation is as defined in 2.4.1.4.; f_j are linear functions. Notice that this formulation is incomplete as the pulp balance equations are not included. For static optimisation over the interval t, the pulp balance equations and storage restraints can be included as:

$$\frac{\text{Min. storage}}{t} \leqslant u_1 + \frac{x_1}{t} - (q_1 y_1 + q_2 y_2) \leqslant \frac{\text{Max. storage}}{t}$$

where x_1 = storage level at the beginning of the interval 3.07

Sequential optimisation over the intervals 1, ...N, results in a minimum storage policy, i.e. the storage is rapidly reduced to, and remains at the lowest allowable level. As there is no cost on the stored pulp, this result is rather obvious.

Application of an unmodified static method thus has two related deficiencies; 1) the resultant minimum storage policy is satisfactory over intervals of low, or average demand, however the occurrence of a peak demand exceeding generation capacity requires either a reduction in system output, or an increase in the NZED maximum demand (the former involves a loss of profit, the latter an increase in cost); and 2) although system operation is optimal with respect to instantaneous conditions, the resultant schedule is not optimal over the total period (N * t).

It can be seen therefore, that this formulation lacks an ability to utilize information on future system behaviour i.e., it lacks a predictive capability.

Three methods of extending this static formulation to give some predictive capability have been considered: 1) artificial storage constraints, 2) recursive (feedback) methods, and 3) feed forward methods.

3.4.2.1. An Artificial Storage Method

Consider defining an artificial minimum storage level, l_a, such that:

$x_{1\,min} \leqslant l_a \leqslant x_{1\,max}$. The value of l_a is chosen to be suitably high to ensure that there is sufficient stored pulp to avert a forced reduction in system output production. The computational procedure is as follows:

1. Choose some value of l_a
2. Perform the sequential static optimisations as above, with the storage constraint:

   $l_a/t \leqslant u_1 + \frac{x_1}{t} - (q_1 y_1 + q_2 y_2) \leqslant$ max. storage/t
3. When a peak demand interval is encountered such that a feasible solution is not possible, reduce the value of l_a until a feasible solution is possible. If this interval value of l_a is below the minimum allowable storage level, return to the start point, increasing the initial l_a value.
4. Increase l_a to its original value, and return to 2.

This algorithm is similar to that presented by Caprez and Caha (23). It gives some improvement on ordinary sequential static optimisation, as it enables the energy system to satisfy peak demands. The resulting schedule is still non-optimal over the total period however.

3.4.2.2. A Recursive Method

Consider a number of intervals making up the period of interest as in the ordinary sequential static method. The recursive method performs sequential static optimisation over each independent interval as before, however, at each optimisation the values of any "slack" in the control variables (i.e. $u_{max} - u_{opt}$) are stored. If in the ith period the demand is such that the control, u, cannot prevent the storage from falling to an unacceptable level, then the algorithm searches back through the (i - 1)th, (i - 2)th etc., intervals taking up the slack in the control variables(i. e. raising the storage level), until the ith period requirements can be fulfilled. Progression to the next interval is then possible.

In implementation, only those variables u which directly influence the storage (or state variable) need be considered explicitly. When recursion occurs, the significant control variables can be forced to their maximum values either by inclusion in the functional equation in a negative sense, or by introducing an artificial minimum storage level which shall be achieved.

The technique is similar in concept to the feedback analogue algorithm of (24) used for the economic operation of a hydroelectric system. Forcing of the control variables in this case is achieved by changing the value of the co-efficient which converts the incremental water rate to an incremental cost. This co-efficient sets the ratio of hydro to thermal generation by means of the co-ordination equations. (59). Thus on the occurrence of spill or excessive drawdown, the algorithm modifies the co-efficient values in preceeding intervals.

This recursive, or feedback method has advantages and disadvantages similar to the artificial storage constraint method; i. e., while it ensures deterministic system production security, it does not ensure overall optimality, especially as it utilises slack in the control variables on a basis of sequential availability rather than cost-effectiveness.

3. 4. 2. 3. A Feedforward Method

An alternative to the feedback type of dynamic algorithm presented above is a dynamic feedforward method developed for this problem. Here, a measure of the loading conditions of future intervals is incorporated in the optimisation at each interval; thus the resultant trajectory has some allowance for known future system behaviour.

Consider two consecutive intervals. If control action in the first interval is such that the resultant storage level is too low for the requirements of the second interval, then in the second interval, two alternative actions are possible:

1. Cut system output production (i.e. paper machine production.
2. Increase grinder production.

Similarly, if the resultant storage level is excessively high, then in the second interval the alternatives are:

1. Increase system output production.
2. Decrease grinder production.

In general, options (1) are not available, and, depending on the mill base electrical load in the second interval, the options (2) may either:

a. Not be possible (owing to plant requirements and N.Z.E.D. M.D. limit)
b. Result in usage of higher cost energy
c. Result in fuller utilization of low-cost energy
d. Result in non-utilization of low-cost energy
e. Result in non-utilization of high-cost energy

Of these of course, (c) and (e) are desirable, (b) and (d) are undesirable and (a) is extremely undesirable, as it implies a production cut.

A scheme was therefore evolved which; when an optimization was being carried out for an interval, assigned a positive or negative cost to the level of groundwood storage at the end of the interval, this cost being based on the predicted electrical mill base load and the paper machine production in the following interval. In this way, the system may be driven such that the cost of energy expenditure is minimized over the two intervals.

Two principal schemes for the costing of groundwood storage level were considered, as follows:

1. Cost the groundwood level continuously such that every possible end of interval level is costed on a basis of its effect with respect to available power and system demands

in the next interval. This method would not be suitable for linear programming as the costing would be non-linear - with discontinuities where, say, the MD limit was broken or another turbine was required.

2. Cost the level on a basis of interpolation between worst and best case costs in the following interval e.g. if the system loadings are all high in the following interval then the worst case is obviously when the groundwood storage is at a minimum at the end of the first interval. Similarly the best case is when groundwood storage is at a maximum at this point in time. The type of interpolation used is governed only by the intended optimisation method - thus linear methods require linear interpolation, whereas non-linear methods allow freedom of choice.

The former method involves difficulties in assigning meaningful costs to every possible end-of-interval groundwood storage level, and so was not pursued further. The latter approach requires only that end-of-interval costs be determined for the extreme storage levels. To determine a reasonable costing basis, consider the effects of the end-of-interval storage level on the operational costs of the following interval. Taking the extreme cases:

1. Groundwood storage at a minimum at the end of an interval. To avoid an enforced reduction in system output in the following interval, grinders must supply sufficient pulp to meet the paper machine demands. The cost associated with this situation is dependent only on the mill base loads of the particular interval. Assuming that all other mill base loads are met, a rather arbitrary costing can be based on the total mill requirement for electricity, i.e.,

   (a) in the case where:

   Total electrical mill loading > (maximum demand) + (generation capacity)

   Cost = (excessive amount) * (maximum demand unit cost for the remaining months of the year - as the maximum demand is automatically raised)

(b) When:

Total electrical mill loading $\leqslant$ (maximum demand) + (generation capacity)

Cost = -(difference) * (unit cost of the most expensive source).

2. Groundwood storage at a maximum at the end of an interval. Again, storage cost at the end of an interval is dependent on the mill base loads of the following interval. Making similar assumptions to (1) above, costings are:

(a) In the case where:

Total electrical mill loading $>$ (maximum demand) + (generation capacity)

Cost = - (difference) * (maximum demand cost per unit).

(b) Where:

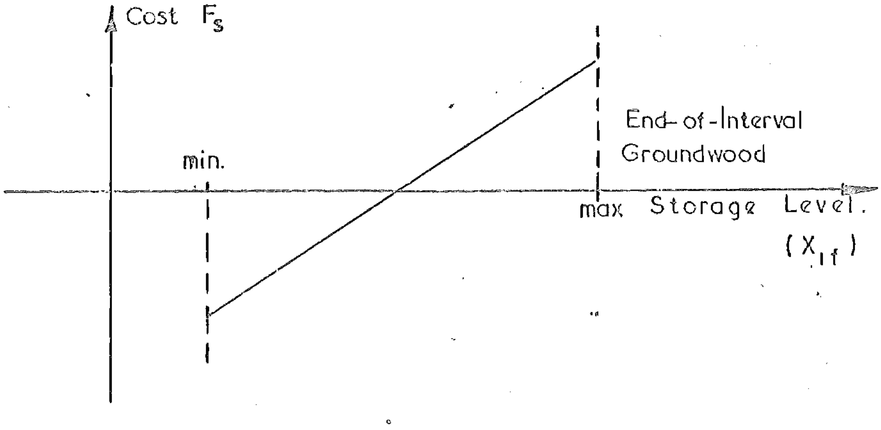
Total electrical mill loading $\leqslant$ (maximum demand) + (generation capacity)

Cost = (difference) * (cost per unit of the most expensive source)

Thus for any given interval, a particular storage cost may be determined by linear interpolation between the above extreme value costs, these being based on the known total electrical loading of the following interval; i.e., storage cost F_s can be expressed as a function of storage level at the end of the interval (x_{1f}), as shown in Figure 3.2

<u>Figure 3.2 Feedforward Groundwood Level Costing</u>

Following interval electrical load, case (b)



i.e. $F_s = c_s x_{1f} + k_1$ 3.08

where: c_s = cost per storage unit

k_1 = constant

The level of storage at the beginning of the interval (x_{1i}) is known, therefore the cost may be expressed as a linear function of groundwood production:

$$F_s = c_s (x_{1i} + u_1 \quad \Delta T) + k_1$$

i.e. $F_s = c_s \ \Delta T u_1 + (c_s x_{1i} + k_1)$ 3.09

where: u_1 = groundwood production rate

ΔT = interval length

This costing arrangement satisfies the requirements of the linear programming method, and can thus be incorporated in the sequential static optimisation approach to give a dynamic capability.

e.g. Define the augmented functional

$$F^* = F + F_s$$

$$F^* = c_1 v_1 + c_2 v_7 + c_3 v_8 + c_4 v_6 + c_5 u_{10} + c_s \Delta T u_1 + (c_s x_{1i} + k_{1i}) \quad \ldots \ 3.10$$

As the initial level of groundwood storage (x_{1i}) is determined in previous interval optimisations, it may be regarded as constant for the interval under consideration: constant terms have no effect on the resultant interval strategy hence may be neglected.

The complete augmented problem is thus;

Minimize:

$$F^* = c_1 v_1 + c_2 v_7 + c_3 v_8 + c_4 v_6 + c_5 u_{10} + c_s \Delta T u_1 \quad \ldots \ 3.11$$

Subject to:

$f_j (\underline{y}, \underline{u}, \underline{v}) = 0 \quad ; \quad j = 2, \ldots\ldots\ldots\ldots, 10$

Min. $\leqslant \underline{u} \leqslant$ Max

Min. $\leqslant \underline{v} \leqslant$ Max 3.12

$$\frac{\text{Min. storage}}{\Delta T} \leqslant u_1 + \frac{x_{1i}}{\Delta T} - (q_1 y_1 + q_2 y_2) \leqslant \frac{\text{Max. storage}}{\Delta T}$$

The initial sequential static optimisation presented at the beginning of this section (see 3.4.2.) has thus been extended to a one-stage predictive or feedforward method, utilizing information on conditions in the next time interval. Further extension to an n-stage predictive method is possible; this is envisaged as a weighted scheme such that for interval i, the groundwood storage cost from interval (n - 1) is of relatively greater magnitude than that from interval n.

Although in this case a linear programming formulation has been developed, non-linear optimisation methods could equally well be applied. A non-linear model could make a closer approximation to the real process, although caution would be required with respect to non-unimodality (i. e. a unique optimum point is required). Any suitable non-linear optimisation method could be used in conjunction with this model.

This feedforward method ideally gives an optimum trajectory while ensuring production security. The ideal is thus an improvement over the feedback and artificial storage methods, having the additional advantage of requiring only a single group of calculations per interval. The latter feature is of considerable advantage for on-line formulations, as it enables calculation of optimum action without detailed calculation of future interval behaviour.

In practice however, optimality and security of trajectories produced is highly dependent on the form and accuracy of the rather artificial groundwood storage costing.

3.4.2.4. Dynamic Linear Programming

The title of this section describes a method involving the static formulation of a dynamic problem, and the solution by linear programming. This method has been applied to a simplified version of the energy optimisation problem.

Consider the schematic model diagram of Figure 3.3. The equations describing the behaviour of this system are:

$$v_1(t) = k_3\, y_1(t) + k_1\, u_1(t) - u_2(t) \qquad \ldots\ldots\ldots\ldots\ldots \qquad 3.13$$

$$x_1(t) = \int_{to}^{t} (u_1(t) - k_2\, y_1(t))\, dt \qquad \ldots\ldots\ldots\ldots\ldots \qquad 3.14$$

$$x_{1\,min} \leqslant x_1(t) \leqslant x_{1\,max}$$

where: $v_1(t)$ = NZED electrical supply $\leqslant v_1$ max 3.15

$u_1(t)$ = rate of groundwood production $\leqslant u_1$ max.

$u_2(t)$ = electrical output of turbogenerator $\leqslant u_2$ max.

$y_1(t)$ = paper machine production rate

$x_1(t)$ = level of groundwood storage

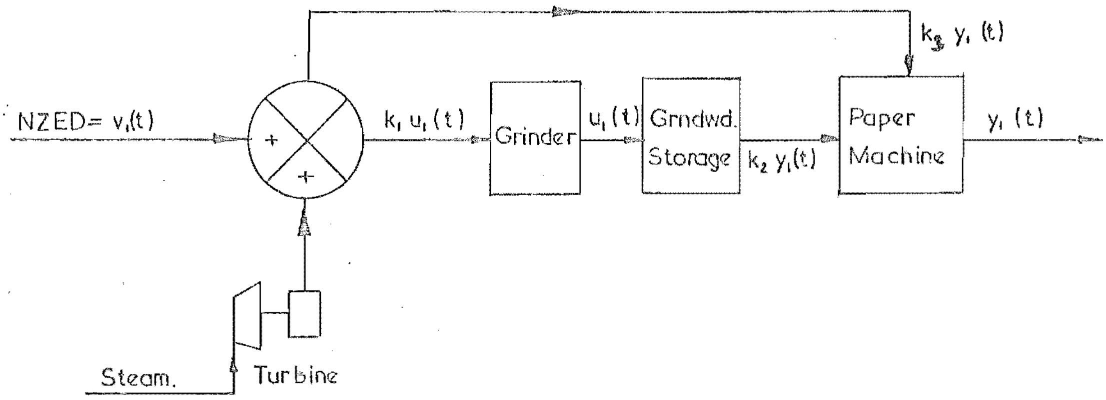


FIG. 3·3 SIMPLIFIED ENERGY OPTIMISATION PROBLEM.

Note that this simplified problem includes the two major characteristics of the total problem, i.e. alternative energy sources and provision for intermediate product storage.

Dynamic optimisation of this system over n intervals can be converted to a static problem (15). Assuming linear transfer functions, the three interval formulation is:

Minimise:

$$c_1 \sum_{i=1}^{3} v_{1i} + c_2 \sum_{i=1}^{3} u_{2i}$$

i.e. $$c_1 \sum_{i=1}^{3} (k_3 y_{1i} + k_1 u_{1i} - u_{2i}) + c_2 \sum_{i=1}^{3} u_{2i} \qquad \text{........ 3.16}$$

Subject to:

(a) NZED maximum demand limit over each interval.

Interval 1: $k_1 u_{11} - u_{21} \leqslant v_{1\,max.} - k_3 y_{11}$

Interval 2: $k_1 u_{12} - u_{22} \leqslant v_{1\,max.} - k_3 y_{12}$

Interval 3: $k_1 u_{13} - u_{23} \leqslant v_{1\,max.} - k_3 y_{13}$ 3.17

(b) Grinder limitations.

$u_{1i} \leqslant u_{1\,max.}$; for all i 3.18

(c) Turbine limitations.

$u_{2i} \leqslant u_{2\,max.}$; for all i 3.19

(d) Groundwood storage minimum limits; let initial level = x_{10}

Interval 1:

$x_{10} + \Delta t(u_{11}) \geqslant \Delta t(k_2 y_{11}) + x_{1\,min.}$

Interval 2:

$x_{10} + \Delta t(u_{11} + u_{12}) \geqslant \Delta t(k_2 y_{11} + k_2 y_{12}) + x_{1\,min.}$

Interval 3:

$x_{10} + \Delta t(u_{11} + u_{12} + u_{13}) \geqslant \Delta t(k_2 y_{11} + k_2 y_{12} + k_2 y_{13}) + x_{1\,min.}$ ... 3.20

(e) Groundwood storage maximum limits

Interval 1:

$x_{10} + \Delta t(u_{11}) \leqslant \Delta t(k_2 y_{11}) + x_{1\,max.}$

Interval 2:

$x_{10} + \Delta t(u_{11} + u_{12}) \leqslant \Delta t(k_2 y_{11} + k_2 y_{12}) + x_{1\,max.}$

Interval 3:

$x_{10} + \Delta t(u_{11} + u_{12} + u_{13}) \leqslant \Delta t(k_2 y_{11} + k_2 y_{12} + k_2 y_{13}) + x_{1\,max.}$ ... 3.21

The above formulation has been solved for the data given in Table 3.2 using a generalised linear programming program developed during the study. The resulting optimal trajectories versus demand values are given in Figure 3.4.

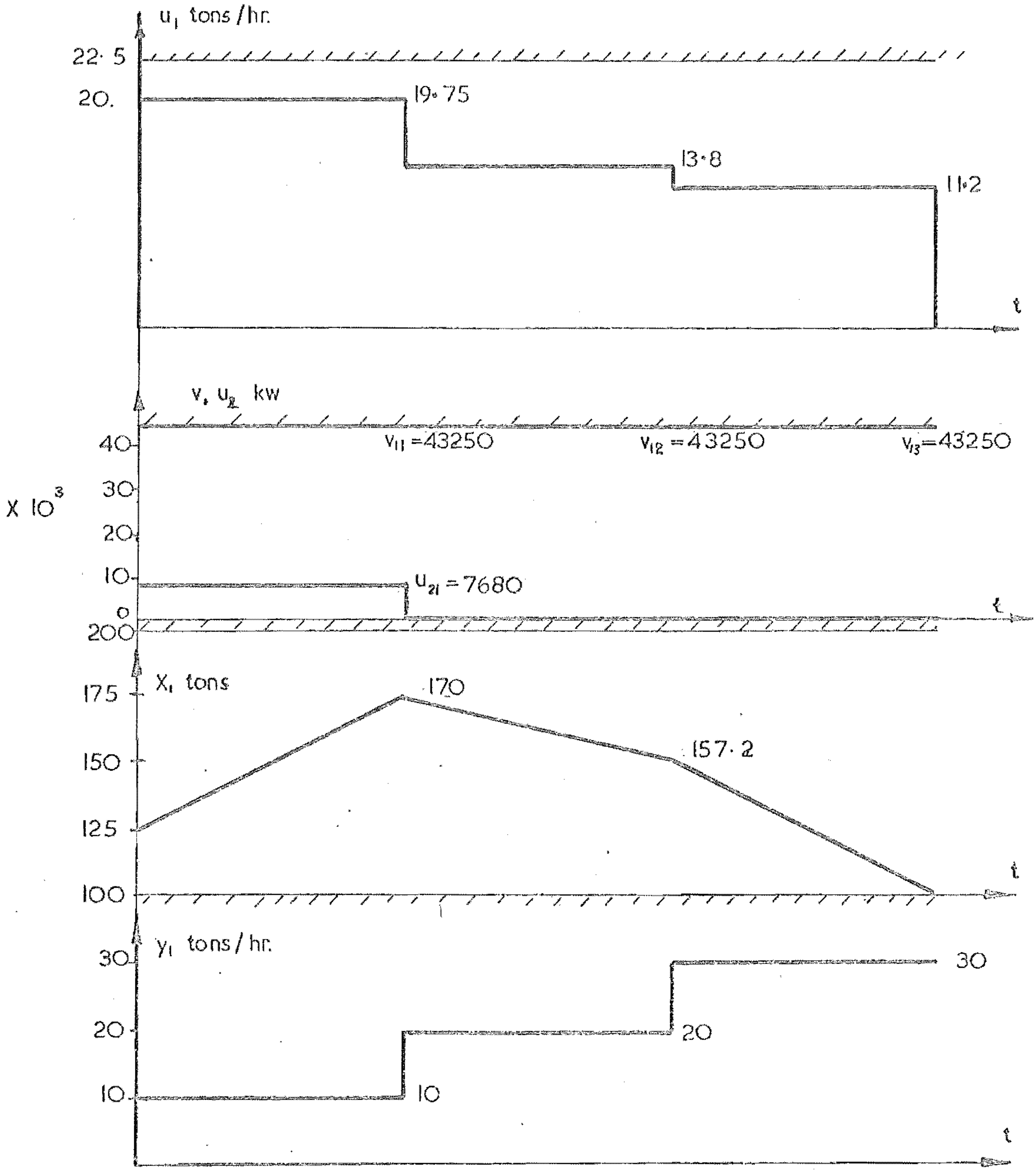


FIG. 3.4 OPTIMAL Vs DEMAND TRAJECTORIES – SIMPLIFIED PROBLEM

Table 3.2 Simplified Problem Data

Parameter Values

Δt	=	4 hours	k_1	=	2280 KWH/ton
u_1 max.	=	22.5 tons/hour	k_2	=	0.85 ton/ton
u_2 max.	=	30,000 KW	k_3	=	590 KWH/ton
v_1 max.	=	43,250 KW	c_1	=	0.0027 $/KWH
x_1 max.	=	200 tons	c_2	=	0.01 $/KWH
x_1 min.	=	100 tons	x_{10}	=	125 tons

y_{11} = 10 tons/hour y_{12} = 20 tons/hour y_{13} = 30 tons/hour

This technique has been utilised by Roefs and Bodin (25) in the optimal scheduling of multireservoir systems. As pointed out, the method enjoys a speed advantage over dynamic programming in the case of multidimensional studies: computational times increasing as the square or cube of the number of matrix rows for linear programming, whereas for dynamic programming the computational time increases to the power of double the number of dimensions. In addition, the technique does not require discrete levels of the state variable, unlike the conventional dynamic programming method. The further two advantages cited by Roefs and Bodin are not applicable to this study.

Unlike the previous extended static methods this technique ensures deterministic system security and optimality. Two features however mitigate against on-line development:

(i) The method gives "one shot" solution of the total period of interest. Consequently, if the system loadings of one interval vary from expected values, a complete solution must be obtained before action can be taken, i.e. the technique has a slow response to disturbances.

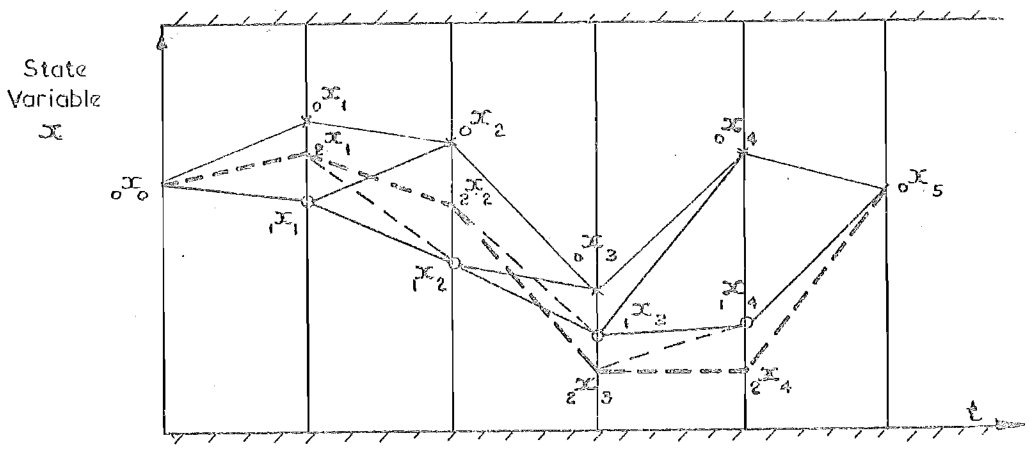
(ii) System conditions are included in the program constraints, rather than as input data to an iterative type algorithm such as dynamic programming. Changes in interval conditions such as system loadings, system parameters or interval length are thus comparatively difficult to implement.

3. 4. 2. 5. A Relaxation Method

This is an extremely powerful approach to dynamic optimisation problems, developed by Fukao and Yamazaki (26) for optimisation of hydro-thermal systems. An initial trajectory is estimated, and a sequence of overlapping two-interval dynamic linear programming problems (of similar form to the dynamic linear programming algorithm of 3. 4. 2. 4.) are solved until the estimated trajectory converges (relaxes) to the optimal trajectory.

Figure 3. 5 illustrates the relaxation process. Suppose the period of interest is divided into a number of intervals, and let the initial estimated trajectory be given by the points ${}_{o}x_{i}$.

Figure 3. 5 A Relaxation Technique



Taking the boundary points as ${}_{o}x_{o}$ and ${}_{o}x_{3}$, determine the optimal ${}_{1}x_{2}$. Repeating this procedure gives the updated trajectory of points ${}_{1}x_{i}$. Updating of trajectories is continued until convergence on the optimal is attained. Although Fukao and Yamazaki use the dynamic linear programming method, any dynamic method could be used.

The power of the method lies in utilization of a priori knowledge of system behaviour. When convergence can be relatively easily obtained (as for the linear examples given in (26)), an optimal solution can be rapidly determined. Use of the dynamic linear programming method in this configuration results in fewer disadvantages than in the "one-slot" solution case, as the repeated two-interval problems have a standard form. Variation of interval length however would be difficult.

The technique only gives a local optimum, and convergence problems could be experienced with more complex (non-linear or non-unimodel) response surfaces. Although this method is more suited to on-line application than a "one-shot" method, a solution over several intervals would still be required before action could be taken.

3.4.3. The Optimal Scheduling Problem - Dynamic Methods

The advantages and disadvantages of the basic dynamic methods are fully discussed in (27). A survey (see 3.2) reveals that although variational methods have been widely used, there have only been a few applications to the type of problem considered here (28, 29). The method of gradients' does not seem to feature explicitly in the literature. On the other hand, dynamic programming in its various forms has been used extensively in the similar hydrosystem scheduling problems (30, 31, 33, 34, 35, 36, 37, 38, 39, 40).

Consequently, bearing in mind the generality and simplicity of the dynamic programming concept, a decision was made to concentrate on the dynamic programming method and its extensions in this study; later work by J. F. Lowinger being aimed at examination and use of the more sophisticated methods.

The principle difficulty in the use of dynamic programming is the dimensionality "barrier". A number of procedures are available which reduce these computational requirements while retaining most of the desirable properties of the standard algorithm. These include successive approximations (41, 42, 43, 44), iteration in policy space (41, 44, 45), quasilinearization (46), iteration about a nominal using successively finer quantization increments (47), and state increment dynamic programming. A comprehensive survey of these procedures is given in (48). The work of Mullis and Roberts (49) is concerned with improving the capacity of dynamic programming through the use of a soft (erasable) memory. Kwakernaak (50) uses a sophisticated concept where the system control policy is based on information continually being acquired from on-line computation. Dynamic programming in conjunction with simulation is envisaged for the optimum-seeking device, however one of the basic ideas precludes a dynamic capability.

These techniques, however, rarely extend the method capability beyond three dimensions.

The alternative approach to reducing the dimensionality problem is to utilize the features of the particular system to be controlled. For example, for linear systems with quadratic performance indices subjected to white Gaussian noise inputs, Sage (51), devises a separation theorem suitable for stochastic optimum controller design.

Development of particular problem features was considered to be the first step to producing a feasible optimisation algorithm, the techniques given above then being utilized as required to further reduce computational requirements. This approach led to the dynamic-static Dynostat Algorithm, and further development was not immediately required. The Dynostat algorithm is presented in Chapter 4.

3.4.4. A Summary of the Algorithms for The Intermediate Term Problems

The preceding sections (3.4.1. to 3.4.3.) have presented attempts to apply existing techniques to the subproblems of the intermediate term level of the total problem hierarchy.

A satisfactory solution procedure was developed for the optimal reordering problem (Section 3.4.1.) by the logical application of standard statistical methods.

Attempts to utilize existing static optimisation techniques to the optimal scheduling problem (Section 3.4.2.) did not meet with the same degree of success. Two algorithms capable of solving the problem were found (i.e. Dynamic Linear Programming, 3.4.2.4; and A Relaxation Method 3.4.2.5.), however these did not fully satisfy the requirements of the total solution structure of Figure 2.12, particularly with regard to an on-line capability.

The computer dimensionality problem of standard dynamic methods precluded their direct application to the optimal scheduling problem (Section 3.4.3.)

3.5 A SUMMARY OF CHAPTER 3

This chapter has examined established techniques for application to some of the subproblems of the overall problem. In some cases, viz. the Static Long Term Optimisation, the Steady State Sensitivity Analysis, and the Optimal Reordering Problem, existing methods were directly applied. For the analysis of the dynamic characteristics of the long term optimal solutions the Monte-Carlo technique was extended to provide the algorithm required. The latter algorithm was developed from work to be described in the next Chapter (4.3), and is a unique application of the Monte-Carlo method. The major advance in the solution of the upper level long term planning problem was one of approach, rather than specific technique. The approach was the iterative solution procedure developed in Chapter 2 (Figure 2.8). Utilizing this procedure, the required solutions to the complex problem could be determined using the comparatively simple specific techniques described in this Chapter.

The Optimal Scheduling problem of the intermediate term level was found to be considerably more difficult to solve. Following the policy of applying the techniques least demanding of computational time and storage first, various formulations of static optimizing methods were attempted. These met with varying degrees of success, the most promising being the relaxation technique developed by Fukao and Yamazaki (26). All methods investigated, however, suffered from some disadvantage with respect to the requirements of the desired algorithm. Dynamic methods were briefly introduced - the dynamic programming method being selected as the most promising. Various approaches to the dimensionality problem associated with this technique were mentioned , however it was decided to concentrate initially on the utilization of the particular features of the problem, rather than refine the solution technique. This approach lead to the development of the new Dynostat algorithm, and associated sensitivity algorithms, that will be described in Chapter 4.

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CHAPTER 4 OPTIMUM CONTROL ALGORITHMS: DEVELOPMENT OF NEW ALGORITHMS FOR THE INTERMEDIATE TERM PROBLEMS

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CHAPTER 4

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CHAPTER 4 OPTIMUM CONTROL ALGORITHMS: DEVELOPMENT OF NEW ALGORITHMS FOR THE INTERMEDIATE TERM PROBLEMS

4.1 INTRODUCTION

The previous chapter described the development of control algorithms from established technique. With reference to the overall problem structure of Figure 2.12, these algorithms provide solutions to:

(i) the long term static optimisation problem

(ii) the long term steady state sensitivity analysis

(iii) the analysis of the dynamic characteristics of the long term optimal solution

(iv) the intermediate term optimal re-ordering problem.

The intermediate term optimal scheduling problem and the associated sensitivity analyses are not amenable to solution using conventional methods. A variety of static and extended static optimisation methods have been applied to the optimal scheduling problem with some success - however, all of the desired features of the required algorithm could not be attained. Section 3.4.3. described the selection of a basic dynamic method, dynamic programming, and its attendant difficulties. The philosophy of utilisation of particular problem features to negate these difficulties was then advanced. This chapter describes the use of this approach to develop a new algorithm, Dynostat, to solve this problem. Also described is the development of various sensitivity analysis algorithms associated with the intermediate term optimum scheduling problem.

4.2 THE INTERMEDIATE TERM OPTIMUM SCHEDULING PROBLEM

4.2.1 Synthesis of the Off-Line Dynostat Algorithm

4.2.1.1 Re-Definition of the Problem

For the model representation shown in Figure 4.1 (a repeat of Figure 2.17), the objective function can be given as:

$$\text{Minimise } C = \int_0^T \left[f(\bar{\sigma}) + g(\bar{x})\right] dt \qquad \dots\ 4.1$$

where the instantaneous cost functions are:

1) $f(\bar{\sigma}) = f(A\bar{S})$ accounting for energy costs; and

2) $g(\bar{x})$ accounting for storage costs,

and where T is the period of time over which the optimum schedule is to operate.

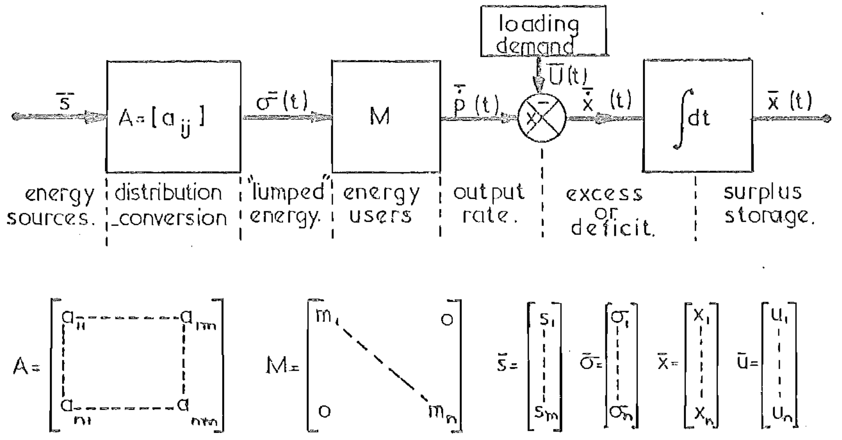


FIG. 4.1 MULTICHANNEL SYSTEM.

At the same time all system requirements are to be satisfied. They are of two types:

1) the constraints given by the system differential equation

$$\dot{\bar{x}} = MA\bar{S} - \bar{u} \qquad \dots\ 4.2$$

i.e.

$$\dot{x}_i = m_i(a_{i1}S_1 + \dots\dots + a_{im}S_m) = u_i,\ i = 1\dots n$$

2) the restraints due to numerous practical limits, of which the following are important examples:

a) storage $O \leqslant x_i \leqslant 1$, say, $i = 1\dots.n$,

b) production rates $O \leqslant \dot{p}_i \leqslant 1$, say, $i = 1\dots.n$

c) energy distribution, i.e., energy used cannot exceed the amounts of energy available, so:

$$O \leqslant a_{1j} + a_{2j} + \dots + a_{nj} \leqslant 1,\quad j = 1\dots.m$$

4.2.1.2 Variables and the Dimensionality Problem

Determination of the optimum schedule requires evaluation of the variables necessary to define the state of the system at any time during the period of the schedule. A sufficient set of such variables is as follows:

1) storage variables $x_1, x_2, \ldots, x_n$; total n

2) energy control variables a_{ij}, $i = 1, \ldots n$ and $j = 1 \ldots m$; total mn.

Of this total n(m + 1) variables, n are dependent by virtue of the n system constraint equations, leaving, therefore, mn independent variables.

The task of determining the optimum schedule may be stated as that of synthesizing a system state trajectory in (m x n) - dimensional, Euclidean space (Fig. 4.2) which, while satisfying the specified restraints and boundary conditions, must also minimise the cost functional over the period of the schedules. The actual assessment of the optimal trajectory could proceed on the basis of the familiar dynamic programming technique. However, as discussed the dimensionality problem of this technique would be severely limiting.

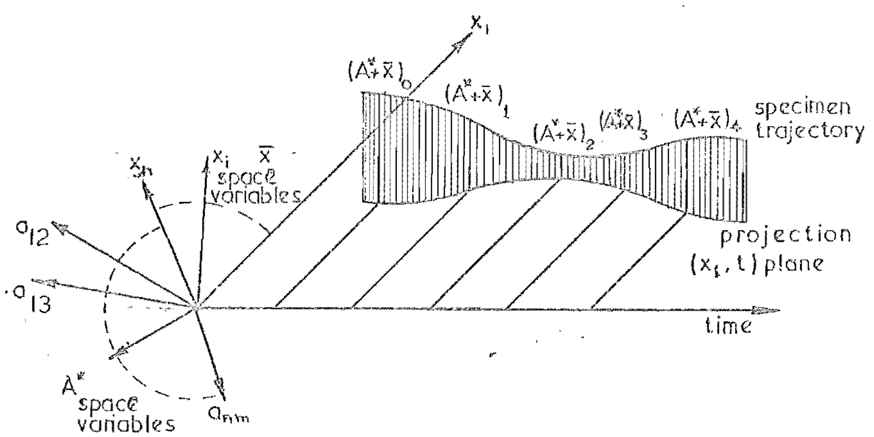


FIG. 4.2 SPECIMEN TRAJECTORY IN $[A^* + \bar{X}]$ SPACE.

For clarity of this explanation (there are technical computational reasons also) it is convenient to choose the n dependent variables from the energy control variables. So the optimum schedule will be assessed in $(A^* + \bar{x})$ space, where $\bar{x}$ space comprises the dimensions $x_1 \ldots x_n$, and where A^* space comprises A space dimensions $\left[a_{ij}\right]$ less n dependent variables, say, $a_{11} \ldots a_{n1}$.

Since exploring all the permissible trajectories in this $(m \times n)$-dimensional $(A^* + \bar{x})$ space would involve a prohibitively large computational effort, it is now desirable to find an alternative technique.

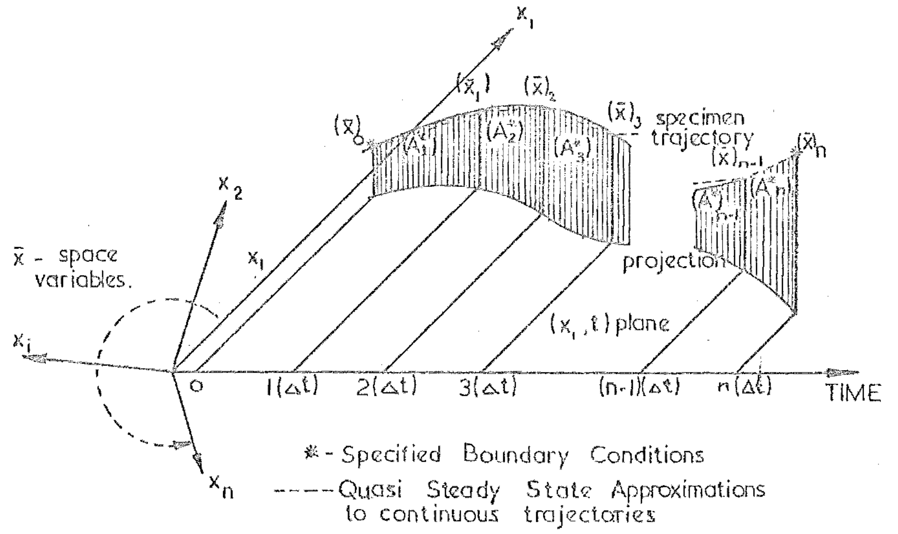
4.2.1.3 Separation into Dynamic and Static Sections

In an assessment of the optimum schedule by progressive construction of an overall optimal trajectory in $(\bar{x} + A^*)$ space, the following observations are made.

1) Each decision on the coordinates for the storage variables affects operational costs at future times, so the assessment of an optimum storage policy must embrace complete storage trajectories.

2) Choice or decisions on the coordinates of the energy control variables affects only instantaneous costs and so the optimum set of control variables at any time is determined without reference to past and future disposition of the overall optimum trajectory in $(\bar{x} + A^*)$ space.

So, considering the operations schedule to be made up of N equal time intervals $\left\{N \Delta t = T\right\}$ in which quasi-steady-state conditions may reasonably be assumed, then for a chosen change of storage coordinates the optimum-seeking exercise within that interval is simply a problem in static optimisation. Choice of the trajectory coordinates in $\bar{x}$ space is part of the dynamic content of the optimisation exercise.



— FIG. 4.3 — STATIC & DYNAMIC SECTIONS IN A TRAJECTORY —

Thus the overall (m x n)-dimensional optimisation exercise (Fig. 4.3) splits into the following two distinct sections:

1) dynamic section (n variables) in $\bar{x}$ space, which requires substantial computer facilities for assessment of complete trajectories;

2) static section (n (m - 1) variables) in A* space, which requires a repetition (one for each interval of each permissible trajectory) of relatively simple static optimum-seeking computations.

This separation into two distinct sections may also be justified by an inspection of the system equations in Section 4.2.1.1. It is seen that dynamic operations in the equations involve only the $\bar{x}$ space variables, so their consideration must belong to a dynamic section of the problem. However, the piecewise linear approximations to the system state trajectories (Figs. 4.2 and 4.3) impose constant values on all components of $\dot{\bar{x}}$ within each interval. So within these intervals the dynamic content of the problem is suppressed and the exercise there, involving only the A space variables, is one of "static" optimisation. Thus identification of the groups of variables may be made directly from the system differential equations.

4.2.1.4 Statement of the Dynostat Technique

The key points of this technique may now be stated as the following:

1) quasi-steady representation of optimal control trajectories.
2) identification of the distinct sections requiring static or dynamic optimisation techniques.
3) the application of a repetition of relatively simple static optimum-seeking techniques in A* space within each time interval.
4) the progressive application of the dynamic programming technique using data from the static optimiser to determine the optimum storage policy for complete trajectories.

A point of interest in the technique is the concurrent operation of the separate DYNamic and STATic Optimisation techniques. Thus the connotation of the title of this "Dynostat" technique.

A practical advantage of the Dynostat technique is a major saving of computer storage and computing time required for assessment of an optimal trajectory. In a majority of applications the static optimum seeking techniques can be expected to be much more economical of computer facilities than dynamic programming. So, by placing a number of system variables in its static section, Dynostat greatly reduces computing requirements. In fact the computer dimensionality problem is reduced from (m x n) dimensions in ($\bar{x}$ + A*) space to little more than that required of an n-dimensional problem in $\bar{x}$ space. Using Dynostat there is no need to examine the economics of all the possible complete trajectories in A* space. Instead, Dynostat in its static mode of operation seeks only the optimum A* space co-ordinates in each quasi-steady interval; no time is wasted on uneconomic configurations - the static optimiser does not consider them.

4.2.1.5 Development of the Computational Algorithm

Corresponding to the N section approximation to the specimen system state trajectory (Fig. 4.3) the computer algorithm must contain N discrete computation stages, which in Fig. 4.4 are shown tackled in the order 1 to N, corresponding to increasing time. At each such stage of computation static optimization assessments are required to determine a multidimensional array of minimum incremental costs $(C)_k$

arising from all the permissible co-ordinate levels of entry and departure of system state trajectories to the kth section. As the computation proceeds through the stages, the arrays of incremental costs are combined in the classic fashion of dynamic programming, and a minimum cost path through all the arrays is determined. The value of the corresponding trajectory co-ordinates and distribution parameters are read out to provide data on the optimum storage policy and energy control settings, respectively. The vector quantities $(\bar{u})_k$ and $(\Delta\bar{x})_k$ in Fig. 4.4 represent forcing function demand levels and trajectory incremental co-ordinates applicable to stage k. The actual computational procedure involved is then essentially as follows.

> The dynamic programming section determines the next incremental trajectory $\Delta\bar{x}$ to a particular grid point $\bar{x}$ which is to be examined, and also sets up the conditions for the static optimum seeking problem associated with this choice of incremental trajectory. The static computational section determines the optimum configuration of the control variables a_{ij} satisfying the system restraints, and then transfers this data on the local optimum to the dynamic section; which in turn costs the incremental trajectory and decides (on the basis of

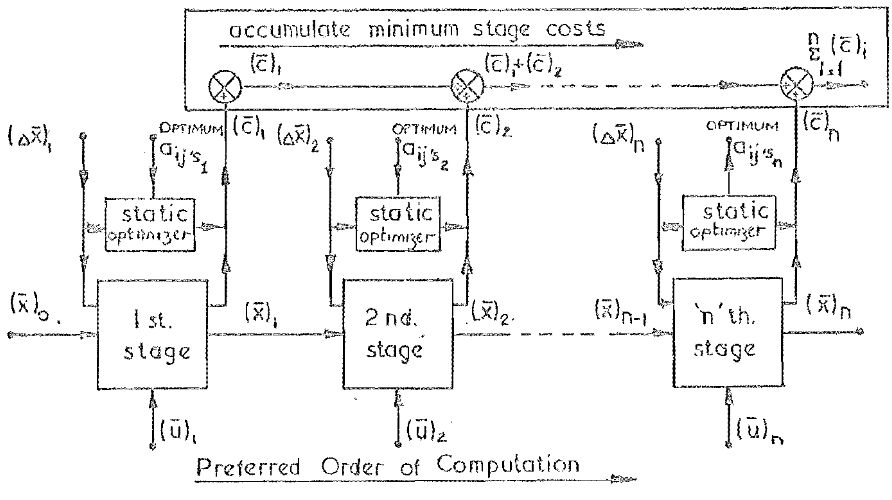


FIG. 4·4 – STATIC & DYNAMIC COMPUTATIONAL SECTIONS.

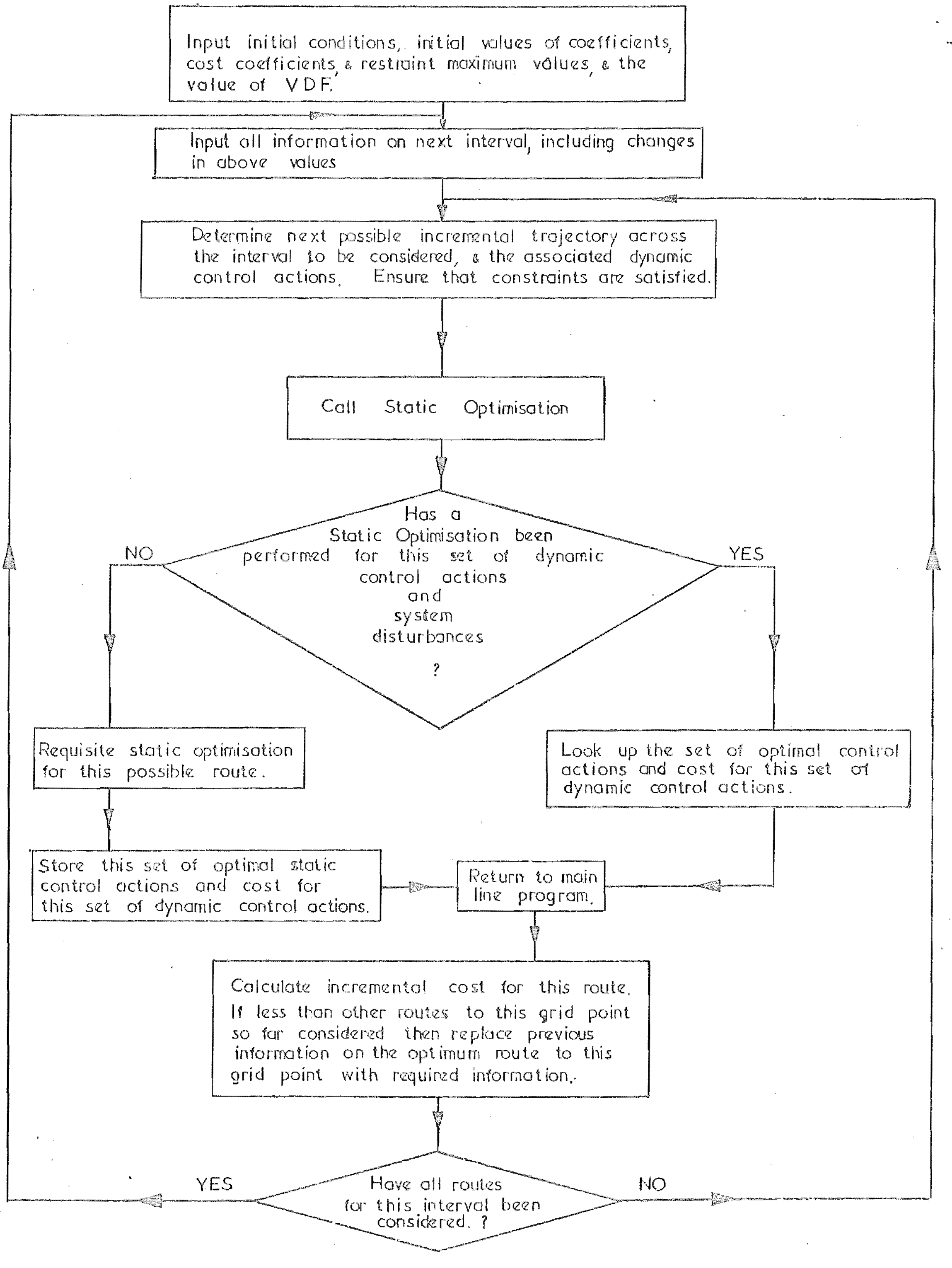


FIG 4.5 DIGITAL COMPUTER ALGORITHM OF DYNOSTAT

the Principle of Optimality) whether to retain or discard this particular route. This procedure is repeated for all permissible incremental trajectories to this grid point, then for all possible grid points at this stage, and finally for all intervals making up the complete trajectory.

A specimen digital computer program flow chart is shown in Figure 4.5. This program has been used to assess optimum energy usage schedules from data on this application as below.

4.2.1.6. Computation Time and Storage

For an (m x n)-dimensional system with r-level discrimination of each spatial variable and N-stage discrimination in time, the total computation time for the dynamic programming technique to assess an optimum trajectory is known to be

$$T_{DP} \doteq N_r^{2mn} t_D, \qquad \ldots\ldots \qquad 4.3$$

where t_D is the time taken to assess an incremental trajectory cost.

Using Dynostat the computation time can be shown to be

$$T_{DS} \doteq Nr^{2n} t_D + \alpha N(2r-1)^n t_S \qquad \ldots\ldots \qquad 4.4$$

where t_S is the time taken to accomplish a static optimisation and α is a carryover factor varying in value between 1/N and 1, depending upon whether all or none of the static optimisation data in one stage is applicable to other stages.

The ratio of the two expressions indicates the improvement in computation time due to Dynostat:

$$\frac{T_{DS}}{T_{DP}} = \frac{Nr^{2n}t_D + \alpha N(2r-1)^n t_S}{Nr^{2mn}t_D} \qquad \ldots\ldots \qquad 4.5$$

$$= \frac{1 + \alpha(2/r)^n (t_S/t_D)}{r^{2n(m-1)}}, \quad m > 1$$

For example, $T_{DS}/T_{DP} \doteq 10^{-10}$ for this application where $\alpha = 1$, $r = 6$, $m = 9$, $n = 1$, $N = 35$, and $t_S/t_D \doteq 10^3$

Savings in computation time for other combinations of m and n are indicated in Fig. 4.6 where $r = 10$, $\alpha = 1$, and $t_S/t_D = 10^3$.

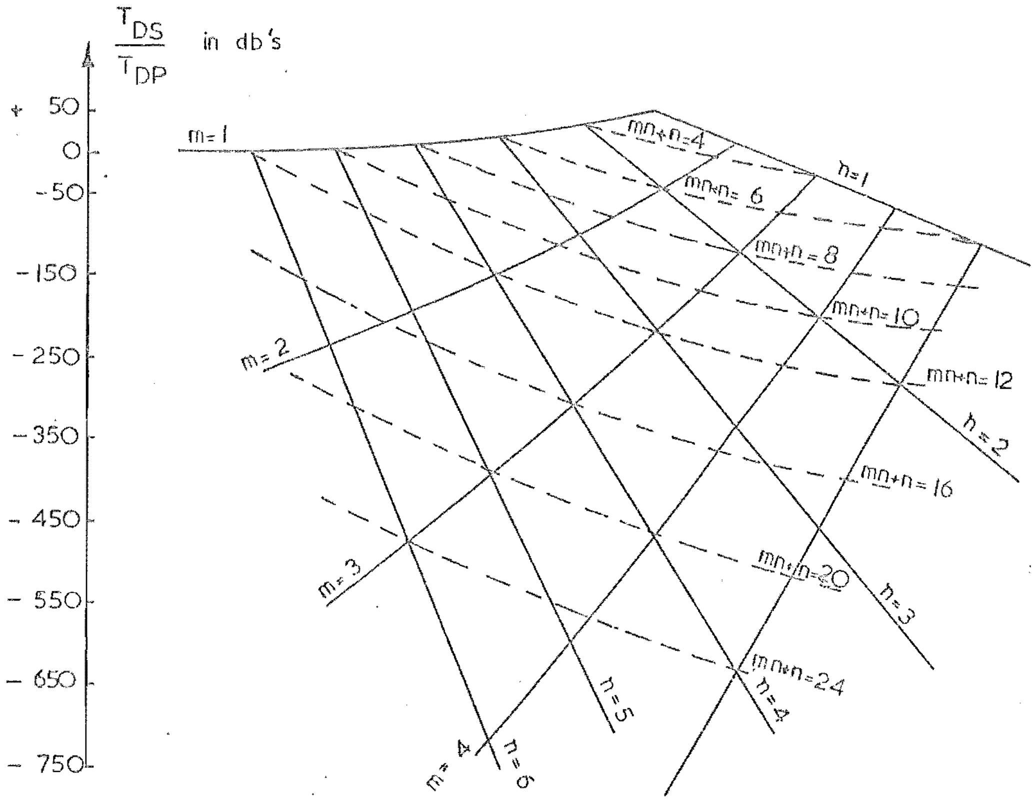


FIG. 4.6 — RATIO OF COMPUTATION TIMES —

In more complex examples the static optimizer would be expected to be slower to converge to an answer point, and then Dynostat loses some of its advantage over dynamic programming. However, with the order of initial advantage indicated in Fig. 4.6 it is quite clear that for the class of problem with ($m \gg n$) the Dynostat technique offers a major reduction in computation time, even when t_S is substantially greater than $10^3 t_D$.

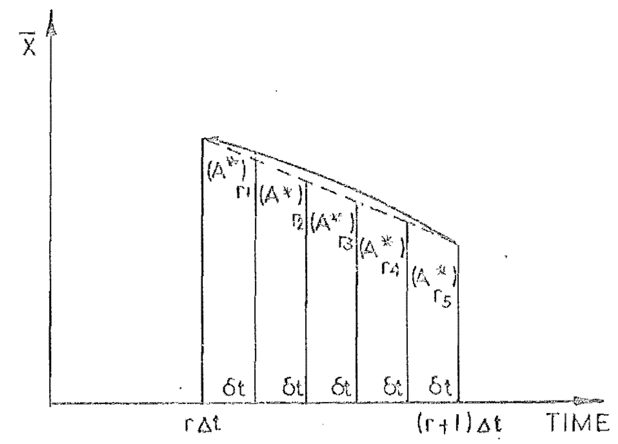
Similarly, it is readily shown that the ratio of storage requirements of Dynostat versus dynamic programming is in substance given by $(1/r)^m$. So for the conditions of the same example Dynostat has an advantage of 10^7:1 with respect to computer storage requirements.

4.2.1.7 The Breadth of Applications

In this discussion it is convenient to use topographical terms in references to the static section of Dynostat. The static optimiser is regarded as a hill-climbing device seeking a maximum value of a profitability functional in A* space (implying a least cost of energy usage). The optimiser, using a predetermined strategy, steers a search point to find the peak of the profitability hypersurface, although it is denied access to certain areas by the system restraints.

1. Systems with Time-Varying Parameters

In principle the dynamic programming technique can always handle time-varying coefficients simply by reducing the stage interval Δt, until for practical purposes the variation of the value of the parameter within the interval may be neglected. However, such reduction of Δt increases the number of stages in the computation and the computational time proportionally.



— FIG. 4.7 — SERIES STATIC OPTIMA —

Rather than incur this computation penalty an alternative is to let Δt be as large as possible subject only to maintaining a satisfactory discrimination of the fastest changes in forcing function demand. A separate and sufficiently fine time discrimination δt is then introduced

(Fig. 4.7) for the static section so that variation of the time dependent parameters in each sub-interval δt may be neglected. The optimum costs from each sub-interval are accumulated over each interval Δt for inclusion in the dynamic section. Thus the increased computation requirement is accommodated where it is expected to hurt least, in the static section of Dynostat.

In quantitative terms an indication of the maximum sizes of the time intervals Δt and δt may be obtained from a consideration of the periodicities present or anticipated in the forcing function input signals, and the fluctuations of the parameter values, respectively. Choosing each time interval a fraction ($\sim$ 1/10) of the shortest periodicity of significant amplitude present ensures that a high per cent confidence level may be placed on an assertion that the computed answer point is within a small percent error of the ideal answer point which is as Δt and $\delta t \to 0$. More precisely, the magnitudes of the time intervals can be predicted from a consideration of the power spectral density functions of the time-varying quantities and the application of sampling theory. However, this is an involved exercise and is invariably avoided in favour of the preceding guideline modified by answer point sensitivity tests during computation proving.

In some circumstances the static optimiser may with advantage be allowed to run continuously seeking the instantaneous optimum in A* space; the total cost over an interval Δt being obtained from it by integration. Subject to noise limitations, a well-designed hill climber may successfully track a static optimum even when topography and restraints are time varying.

2. Nonlinearities and Switching Discontinuities

The dynamic programming technique is again well-suited in principle to handle non-linear functions and restraints. However, the effect of nonlinearities in the static section is to complicate the topographical structure of the hill-climbing exercises leading to a slower convergence to an answer point. Answer point ambiguities due to multiple peaks and a possible re-entrant restraint structure may also be encountered. Dynostat accommodates nonlinearities with a degree of efficiency dictated primarily by the quality of the hill-climbing technique chosen from the wide range of such techniques available.

Switching discontinuities occur frequently in exclusive either/or situations where either this machine or another but not both machines may be used to manufacture a certain product. In the dynamic section solutions are readily obtained by defining and suitably restraining switch variables in a well-established technique.

The particular application included switched elements in the static section. They were handled simply by repeating each run for each permissible combination of switch positions, and routing cost information on the best combination to the dynamic optimizing section. More efficient schemes which avoid the need to reset between runs are clearly possible.

3. Extensions of the Introductory System Model

The simplified system model of Fig. 4.1 served as a suitable example with which to introduce the essentials of the Dynostat technique. Practical problems do not appear directly in this simple form due to many complicating features which would enter into a flow diagram model such as intermediate cross-channel couplings and equipment time constants.

If the system is linear, then it can be shown that such feedbacks and cross-channel couplings can be compounded and the flow diagram representation remains essentially unchanged from Fig. 4.1 although overall feedback may be present in some cases. (For the example illustrated such unlikely feedback would have to be a derivative function to have physical significance.) The order of the characterizing differential equation is unaltered, only the matrix co-efficients become more involved. Even when non linearities are present it is considered that the principles of Dynostat remain valid. Additional complication due to non linear function evaluation is, of course, incurred.

However, the omission of an equipment time constant (say, a generator with an exponential time constant τ seconds) could have serious repercussions in a case where it is important to follow fast changes in forcing function demand. In such cases ($\Delta t \leqslant \tau$) the necessary inclusion of equipment dynamics adds to the computation problem.

4. Extensions Beyond the Class of the Present Model

Although the Dynostat approach to optimization is expected to be of value in other classes of systems, the detailed work reported here pertains only to the class of system outlined in Fig. 4.1 together with the variations discussed in Sections (1), (2), (3) above.

A preliminary examination, however, shows that a similar approach to the classic optimal control problem is an aid to comprehension and computer implementation of this optimisation problem.

(i) The static section of the approach recognises the maximum principle in topographical terms, viz., a search point finds the co-ordinates of the optimum instantaneous forcing function in state space at an extremum of the engineering Hamiltonian's hyper-surface, although system restraints deny access to parts of this hypersurface. Clearly, this section of of the problem can be considered as a hill-climbing exercise and amenable to so-called static methods of computer implementation.

(ii) The dynamic section caters for time-varying changes in the hypersurface topography due to the Hamiltonian formulation and possible presence of time-varying system co-efficients. Imposition of quasi-steady approximations as in Fig. 4.3 would result in the dynamic section assessing from and scheduling to the static section the changes of topography progressively across the time intervals. Dynamic programming (or multistage decision making) does not seem to be involved unless all feedbacks of a state variable are absent, i.e., there is an open loop integrator in the system topology.

In this area of generalisation of the Dynostat approach additional research is being carried out.

4.2.1.8 Application to the Practical Problem

The initial mathematical model of the system is as described in Chapter 2.4 and embodied time variance of demand and some conversion co-efficients a_{ij}, and an assumption of linear transfer functions for the blocks of the model block diagram.

As the initial model was taken as linear, the Dynostat program was constructed to use dynamic programming for the dynamic section and linear programming for the static section.

Using this program, optimum schedules were produced for a period of one month (daily intervals). It was found that the scheduling allowed better use of the state electricity supply such that the maximum demand figure necessary to avoid failure to satisfy production demands could be reduced. Fig. 4.8 illustrates the saving (for each value of this parameter) produced by the optimum schedules as compared with mill operation as actually occurred, a special program computing actual operating costs on an identical price structure. The values of saving pertain only to the elementary linear model of the plant. A sensitivity analysis is also necessary to assess a sufficient margin for probabilistic disturbances.

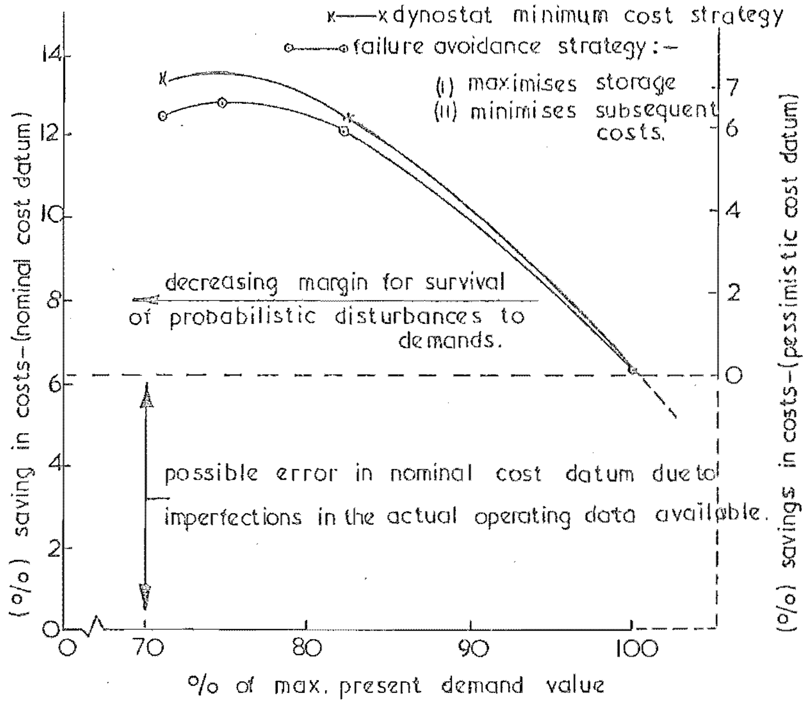


FIG. 4.8 - COST RATIO CHARACTERISTIC

Note the reduction in comparative saving as the maximum demand is reduced towards the minimum; this is due to the plant being forced into more uneconomic operating conditions to avoid production reduction.

Using an IBM 360/44 the computation time to produce a schedule for the 35 daily intervals at this 20 percent discrimination on the single-dimension storage was approximately 25 minutes. This was with extremely full output, which slowed computation greatly. In fact, the actual computation time would be of the order of 10 minutes.

4.2.2 Synthesis of the On-Line Dynostat Algorithm

4.2.2.1 On-Line Requirements

Consider the case where off-line optimum schedules have been produced for the coming period. The general on-line requirement is for a fast response algorithm to update these schedules in the light of new system information or revised loading schedules. Generally, such information, or revision (referred to as disturbances) apply to only a few of the total number of intervals in the schedule. Three general classes of disturbance may be determined, in order of priority with respect to speed of response requirements, as shown in Fig. 4.9

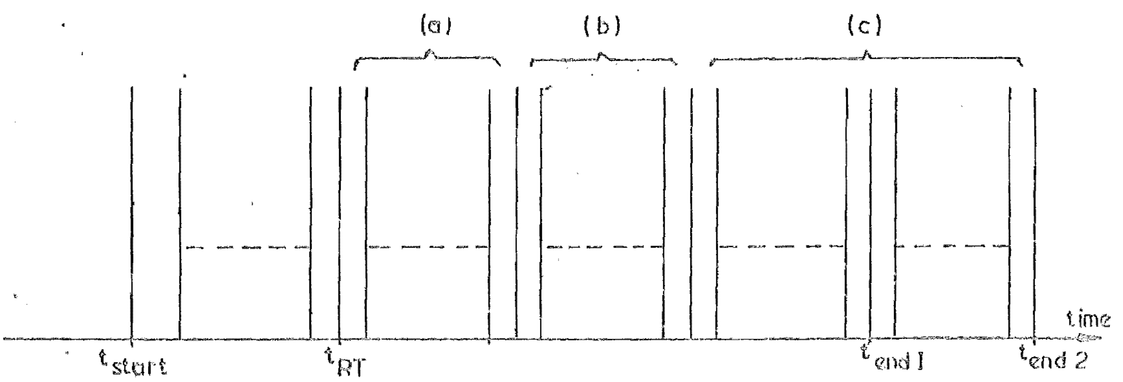
i.e. Taking a real time reference as r_{RT}, (See Fig. 4.9) the disturbance applies to;

(a) the immediate next few intervals

(b) some intermediate group of intervals

(c) intervals at the end of the schedule, or additional intervals beyond the off-line schedule. i.e. extension of the optimum schedule planning horizon.

Response requirements obviously become less stringent from (a) to (c) owing to the buffering action of intervening intervals, i.e., a disturbance of type (b) or (c) will have a smaller effect on the action required at t_{RT} than will a type (a) disturbance.



— FIG. 4.9 — ON LINE DISTURBANCE CLASSES. —

4.2.2.2 Inadequacies of the Off-Line Algorithm

As discussed above, the off-line algorithm has two major sections; a) dynamic and b) static. The dynamic section forms the main-line program, and the static section forms a sub-program called by the main-line program whenever a minimum stage cost policy is required (see Fig. 4.4). Because the static section is a unitary subroutine slaved to the main-line program, improving the response time of the static "package" can be treated as a separate exercise. Owing to the difficulty in significantly increasing the speed of this relatively efficient subroutine on the digital computer, the alternative approach of reducing the frequency of usage was pursued in this study. Analogue computer techniques have been utilised with considerable success to achieve the former objective. This work was undertaken by T. W. Marks as a part of the overall project.

The dynamic section utilises the implicit recurrence relation of dynamic programming in sequentially extending r optimal trajectories from one fixed boundary point through r time variable boundary points (r is the number of discrete state variable levels). Only at the last interval in the planning horizon are the r trajectories brought to the other boundary point to identify the optimal solution to the given two-point boundary value problem. This mechanism is identical whether computation proceeds in a forward direction (as in Fig. 4.4) or in the reverse direction.

In the on-line situation where only a few intervals are disturbed, the calculation must proceed through all intervals in the schedule before the updated optimal trajectory can be determined. As conditions for the majority of the intervals in the schedule have not been affected by the disturbances, such a procedure involves a large degree of repetitive calculation. If the algorithm could be so organised that relevant information on the optimum trajectories across each interval could be succinctly stored, a large proportion of the repetitive calculation could be eliminated. This would significantly improve the response time of the algorithm.

4.2.2.3 On-Line Algorithm Concepts

The basis of the on-line algorithm is a modified statement of Bellman's "Principle of Optimality" (1)

With respect to Fig. 4.10 the original "Principle of Optimality" can be phrased:

> "If (UV) is the optimal trajectory between boundary points x and z, then; (U) is the optimal trajectory between points x and y, and (V) is the optimal trajectory between points y anx z."

Consider the modified statement:

> "If trajectory (U) is optimal with respect to the points x, y, and trajectory (V) is optimal with respect to the points y, z, and y is the optimal of all possible states at the time t_n (with respect to the total functional value); then the trajectory (UV) is optimal between the boundary points x and z."

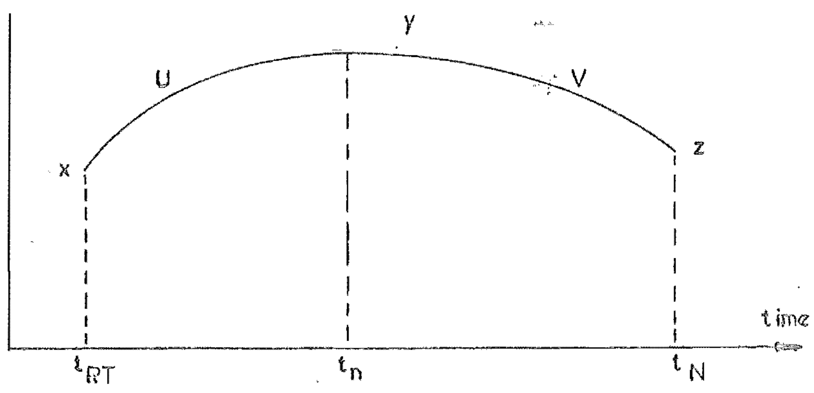


FIG. 4.10 – SUBDIVISION OF OPTIMAL TRAJECTORIES.

This modified statement can be utilised directly in an on-line algorithm for disturbance classes (a) and (c). For the case of an (a) type disturbance optimality has been lost for the (U) section of the trajectory illustrated; however information on the r optimal trajectories (V) from the allowable states y at time t_n, to the endpoint z is still valid. (This information is obtained where the original off-line calculation is performed in a reverse direction, t_N to t_{RT}).

The on-line algorithm computes the r optimal trajectories (U) from the initial point x to all allowable states y. The optimal trajectory xz is then given by:

$$\operatorname{Min}_y \text{ (Max) } \left(C_{xy} + C_{zy}\right) \qquad \ldots\ 4.6$$

where C_{ij} = cost of optimal trajectory from grid point i, to grid point j.

Alternatively, the on-line algorithm could proceed as the conventional "backwards" dynamic programming from the states y to the initial state x, given the optimal costs C_{zy} as initial data.

The most frequent case of this type of disturbance involves only one interval. Obviously the response time of the on-line algorithm is extremely fast in this case as only r static optimisations need be performed to obtain the new optimal trajectory.

For the case of a (c) type disturbance a similar procedure applies. Assuming that C_{xy} information is available, the algorithm proceeds as forward dynamic programming from the allowable states y to any final state z, with C_{xy} as initial data.

The case of a (b) type disturbance is a little more complicated as three trajectory segments have to be "matched", rather than two as before (Fig. 4.11). Two equivalent alternative methods are possible: 1) apply forward dynamic programming from the initial states x (with C_{wx} as initial data) to all states y, then select the optimum state y which gives $\operatorname{Min}_y\text{(Max)}\left[C_{wy} + C_{zy}\right]$ as above; 2) use "backwards" dynamic programming from initial states y to states x and apply a similar selection.

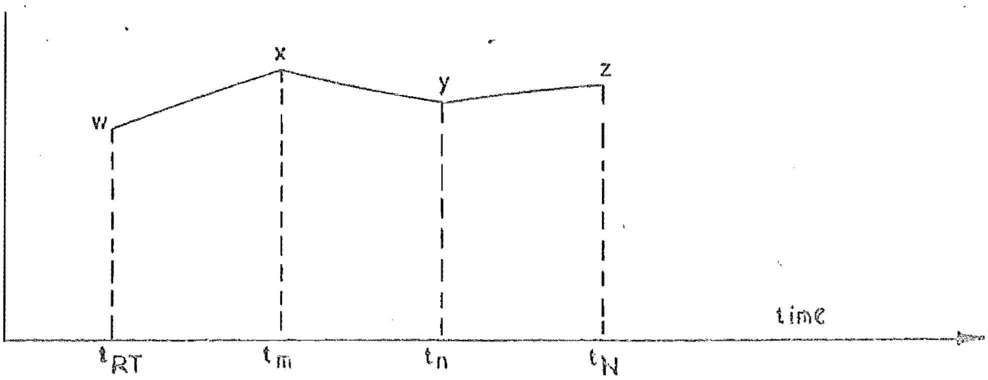


FIG. 4.11 — THREE TRAJECTORY SEGMENTS - A CASE [b] DISTURBANCE

4.2.2.4 Implementation of the On-Line Algorithm

The basic computational "unit" used in all three cases above is the dynamic programming (or dynostat) calculation involved in stage progression (see Figure 4.4) i.e., the calculation involved in determination of the minimum $\sum_{i=RT}^{n} C_i$ for all allowable states y at t_n, given the minimum $\sum_{i=RT}^{n-1} C_i$. As this computational "unit" is derived from the conventional off-line algorithm, with suitable organisation of calculation sequences a single program should perform all functions (i.e., off-line and on-line optimisation). A program conforming to this specification has been written, salient developments being briefly described here.

A primary initial requirement was for a flexible method of storing, accessing and updating all current optimum route and cost information using minimum computer storage.

Four techniques for storing the required route information were considered:

1. Store all possible incremental trajectories and the associated costs, "activating" those currently optimum. This technique was not considered further owing to the tremendous amount of storage required.
2. Use the "linknet" technique of Cashin, Mayson and Podmore (2). This is a list programming technique developed for graphical analysis. Three information files are maintained; one for information regarding the nodes of the graph, one for information regarding the arcs joining nodes together, and one for beads, which link particular arcs with particular nodes. Each file is subdivided into a large number of numbered "blocks", each "block" defining the attributes of a particular node or arc, or in the case of beads, relating the nodal and arc "blocks". This technique is more general in application than is warranted for this particular case as here the nodal layout is very

regular, r per time interval, where r is the number of discrete storage levels, and also because there are only (2r - 1) unique incremental trajectories (arcs) per time interval. Use of this technique directly would therefore result in superfluous information being stored in both the arc and bead files. Development of a similar technique tailored to the particular application was favoured however.

3. Use of list programming with two information files; one defining the (2r - 1) possible incremental costs for each time interval, the other subdivided into tagged blocks giving the node attributes in addition to pointers showing the next and previous nodes on the optimum route. The disadvantage associated with this approach is that the possibility of multiple optimum routes cannot be allowed for (i.e. multiple pointers) without defining the nodal blocks large anough to allow for the maximum number of pointers; from previous optimum nodes (r), and to the next optimum nodes (r). Thus in the case of a single optimum route, 2(r - 1) storage positions within each nodel block are wasted.

4. Use of list programming with multiple matrix files. As in (3) above, one separate file is used to define the (2r - 1) possible incremental costs per time interval. The remainder of the matrix files each describe a particular node attribute; the matrix index defining the particular node being described. For a single optimum trajectory over N time intervals, (rN) elements would be required in each nodel definition matrix file: the possibility of multiple routes requires that a greater number of elements be provided. The presence of a multiple route radiating from a given node is indicated by a number at the corresponding index in

an additional identical file defined for this purpose. The value of this number ($\geqslant rN$) gives the index at which complete nodal information on this additional route may be found. By ensuring that redundant information is removed from these additional levels ($\geqslant rN$) in the information files, multiple routes can be allowed for without the same degree of wastage as in (3) above.

The method developed in (4) above was considered most suitable for this application and was used satisfactorily in an IBM 360/44 implementation of the on-line Dynostat programme (See Fig. 4.12). The regular layout of nodes on the dynamic programming grid allows a repeatable numbering system to be used - the index number related to each node can thus be determined by a simple program and an additional file is not required. The case of a non-valid node can be indicated by zeros in all associated nodal attribute files.

Six nodal information files or column matrices were defined for this particular application, these describing: a) optimum cost to the boundary point at the end of the time horizon under consideration, b) optimum cost from the initial point at the beginning of the time horizon, c) the index corresponding to the next node on the preferred optimum route, d) the index corresponding to the last node on the preferred optimum route, e) the index corresponding to the storage location of a, b, c, d, e, and f information for an alternative optimum route in the forward direction, and f) the index corresponding to the storage location of a, b, c, d, e, and f information for an alternative optimum route in the reverse direction. A zero element in e, or f indicates that there are no further alternative optimum routes.

The broad requirements of the on-line algorithm were given in 4.2.2.1, and the basic algorithmic concepts for satisfaction of these requirements were presented in 4.2.2.3. Although the basic computational "unit" involved in this exercise is comparatively simple, program organisation and housekeeping (e.g. updating values of C_{wxyz} following a disturbance type (a), consequent C_{xw} recalculation and action) require a complex structure of subroutines. The program developed has been designed to perform only the dynamic optimisation functions, the static optimisations for the (2r - 1) possible $\dot{x}$ values in each interval not being pertinent to the on-line program in that they can be performed by a separate subroutine which can be called for when required (e.g. the linear programming "package" of 3.3.1 or 3.4.2.4).

The final program has a four level hierarchical structure - a descriptive representation of the various subprograms and their functions being given in Figure 4.12. The four levels as shown comprise: a) Program mode selection determined by disturbance type or required action, b) an organisational layer to direct lower level operations, c) direct control of cyclic basic operations, and d) basic operations. The functions of the subroutines at each level of the program are given in Figure 4.12 and will not be further elaborated here. The list programming technique developed for this application and described in (4) above was used to minimize storage requirements while allowing ready access and modification to optimal routing and costing information. The present function selection routine requires a high degree of operator interaction in its present form in that the operator is required to recognise the type of disturbance, and input necessary data and calculation and output limits. Certain housekeeping and output routines such as STEPPROG, RESET, INFOUT, and GRIDOUT also require direct operator request. This is in keeping with the nature of the program - operator intelligence being utilised for functions it best performs in direction of the computer, the latter handling functions for which it is better equipped. In an on-line computer situation this philosophy would not substantially change, however more automation in terms of date acquisition, handling, and output would be desirable and could readily be implemented.

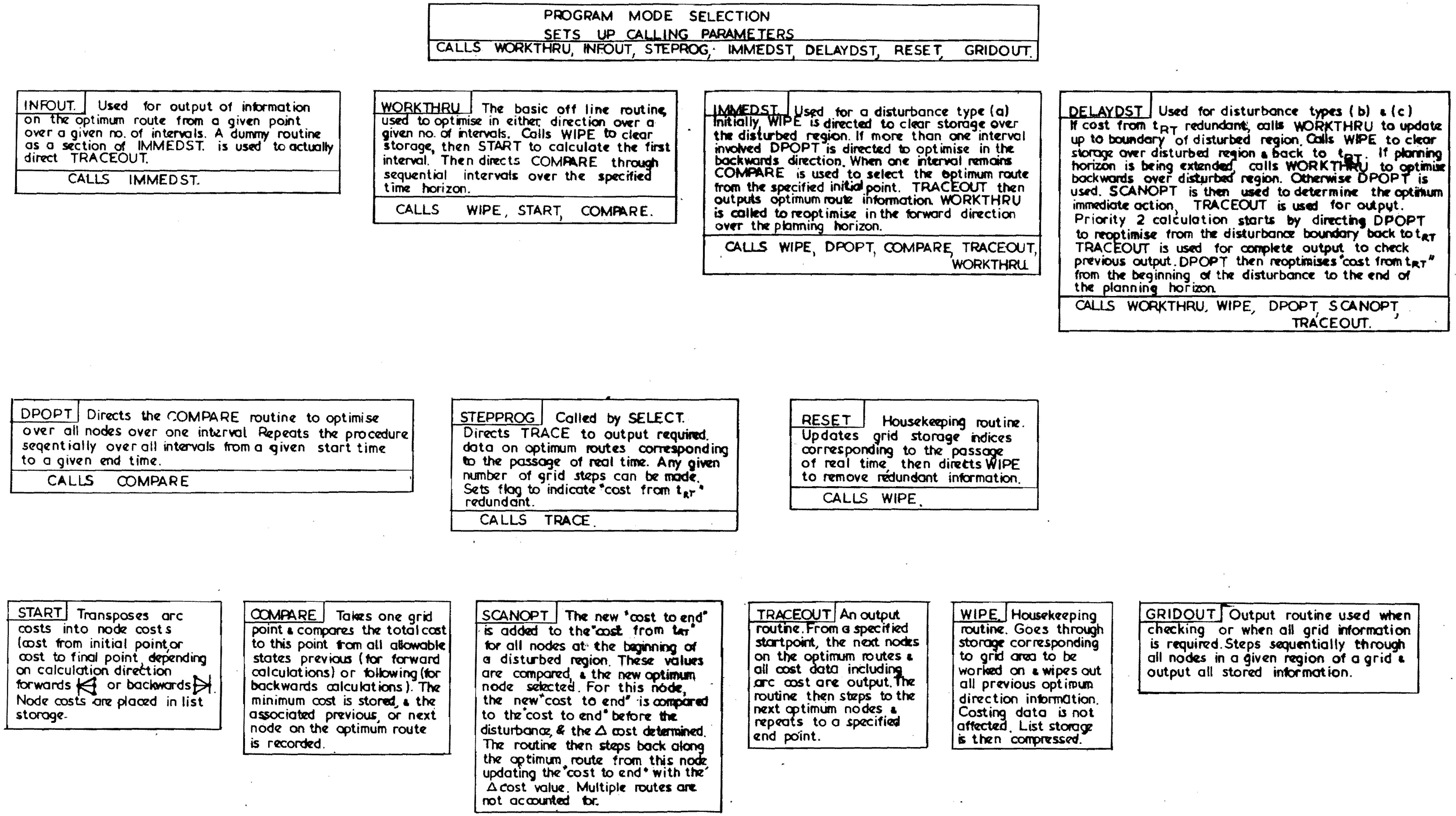


FIG. 4.12 HIERARCHICAL STRUCTURE OF SUB-PROGRAMS FOR THE ON-LINE DYNOSTAT PROGRAM.

Development of this composite program completes the major work carried out on the "optimal scheduling problem" of the intermediate term layer. The requirements for a fast response dynamic optimisation algorithm as discussed in 2.3.2. have been realised.

4.2.3. A Proposed Heuristic Dynamic Optimisation Algorithm

Although further algorithm development was not considered necessary for the energy optimisation problem, computing speed increases of several orders of magnitude may be necessary for cases with multidimensional dynamics. Using the dynamic programming technique as a basis, the obvious way to achieve such a speed increase is to drastically reduce the number of optimal route possibilities considered at each stage in the calculation. Although the techniques discussed in 3.4.3. seek to attain this object, none achieve the order of reduction required to enable use of the method on more than two or three dimensional systems. A more promising method would appear to be based on a heuristic algorithm which utilizes the experience gained in the operation of the particular system under study. The trajectory determined by such a process would not be the absolute optimum, rather, a near optimum trajectory would result. If computation time were included in the objective function, then for large dimension systems a suitable heuristic algorithm could be considered optimal with respect to the extensive search dynamic programming algorithm.

The basic problem or routine of this heuristic algorithm is: given that the "optimal" trajectory so far results in a system state $\underline{X}_i$ at the beginning of interval i, and given the set $\underline{L}_k = \left[\underline{L}_i, \underline{L}_{i+1}, \underline{L}_{i+2}, \ldots\ldots, \underline{L}_{i+k}\right]$ of m-dimensional loading sets for the future intervals within the algorithm planning horizon (k intervals); determine the "optimal" n-dimensional action (or control) set $\underline{U}_i = \left[U_{1i}, U_{2i} \ldots\ldots\ldots, U_{ni}\right]$ for the interval i. This action set extends the optimal trajectory to the n-dimensional point $\underline{X}_{i+1}$, where the problem or routine is repeated.

Ideally the algorithm would operate utilizing some function f;

$$\min_{\underline{U}_i} \; C_k = f(\underline{L}_k, \underline{X}_k, \underline{U}_i) \quad \ldots\ldots\ldots \quad 4.7$$

where; C_k = trajectory cost over the intervals i, i+1, i+2......, i+k

$= C_{i+k} - C_i$

where; C_i = trajectory cost from initial point to beginning of interval i.

Generally the function f would be extremely complex, and partially indeterminate, precluding conventional optimizing methods. Hence a heuristic optimisation algorithm.

To simply describe the proposed algorithm define the mappings:

$$\begin{aligned} A &: \quad \underline{L}_k \rightarrow \hat{l}_k \\ B &: \quad \underline{U}_i \rightarrow \hat{u}_i \\ C &: \quad \underline{X}_i \rightarrow \hat{x}_i \end{aligned} \qquad 4.8$$

where; (i) $\hat{l}_k$ is a scalar variable representing the "stress" to be imposed on the system in the k future intervals of the planning horizon.

(ii) $\hat{u}_i$ is a scalar representing the system resources disposed in interval i to "oppose" this "stress".

(iii) $\hat{x}_i$ is a scalar representing the remaining system resource "potential" available at the beginning of interval i.

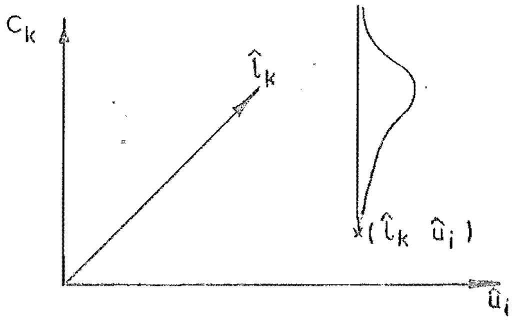


FIG. 4·13 - PROBABILITY DISTRIBUTION FOR PROPOSED HEURISTIC ALGORITHM

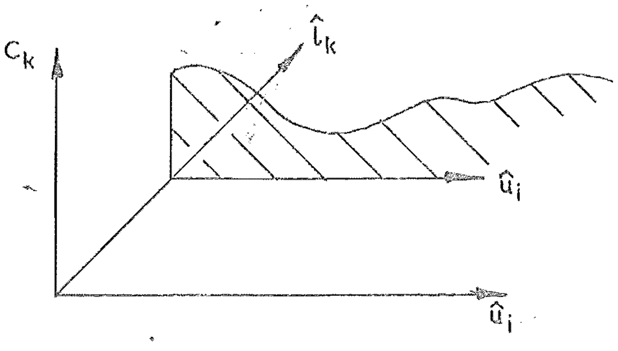


FIG. 4·14 - SIMULATED COST-VERSUS - CONTROL ACTION

The algorithm may be divided into two sections:

(a) $$\underset{\hat{u}_i}{\text{Min}} \quad C_k = f_1\,(\hat{l}_k,\ \hat{x}_i,\ \hat{u}_i). \qquad \ldots\ldots \quad 4.9$$

The function f_1 is again complex and partially indeterminate. In the course of computation over some long period a probability distribution representing the function f_1, is built up. This distribution can be illustrated for any pair $(\hat{l}_k,\ \hat{u}_i)$ as in Fig. 4.13. $\hat{x}_i$ would be another variable in a practical algorithm - it has been neglected here only for clarity of illustration.

(b) $$\underset{U_1 \ldots U_n}{\text{Min}} \quad c_i = f_2(\underline{U}_i,\ \underline{X}_i,\ \underline{L}_i) = f_2\,(U_{1i},\ U_{2i} \ldots U_{ni},\ \underline{X}_i,\ \underline{L}_i) \qquad \ldots\ldots \quad 4.10$$

subject to: B: $U_i = \hat{u}_i$

i.e. $$g(U_{1i},\ U_{2i},\ \ldots\ldots\ldots U_{ni}) = \hat{u}_i \qquad \ldots\ldots \quad 4.11$$

This optimizing procedure is effectively the reverse mapping B^{-1}, thus the function f_2 is a deterministic control costing, and conventional static optimizing methods can be used. c_i is the actual cost across interval i resulting from action $\underline{U}_i$.

The computational procedure of section (a) involves Monte Carlo analysis (52, 53) and hill climbing optimisation as follows:

1. Perform the mapping A to determine $\hat{l}_k$ for the ith interval.
2. For each allowable value $\hat{u}_i$ generate a random number and perform a Monte Carlo selection of a particular C_k from the "learned" distribution of Fig. 4.13. This generates a simulated cost response curve as shown in Fig. 4.14.
3. Using a suitable hill climbing method, select the "optimum" $\hat{u}_i$ from the simulated cost curve of 2.
4. Perform the optimisation of section (b) to give the optimum control $U_{1i},\ U_{2i},\ \ldots\ldots U_{3i}\ \ldots\ldots U_{ni}$ for the ith interval. Optimum $f_2\,(U_1,\ \ldots\ldots,\ U_n) = c_i$ = actual cost across interval i.
5. From process relationships determine the value $\underline{X}_{i+1}$ for the next interval.

6. Return to 1 and repeat until the desired planning horizon is reached.
7. When the interval $i + k$ is reached, the actual cost C_k can be determined. This is used to update the distribution for interval i. Note that the decisions at intervals $i, \ldots\ldots, i + k - 1$ each influence the value of C_k; hence the C_k distribution obtained is not a unique basis for the ith decision. Reduction of this cross coupling would result in faster, more accurate "learning". This could possibly be achieved by computing the value of C_k on the basis of:

$$C_k = c_i + s_{i+1} + s_{i+2} + \ldots\ldots + s_{i+k} \quad \ldots\ldots 4.12$$

where s_{i+j} = actual cost across interval j resulting from some given standard decision.

This procedure can be likened to the standard experimental procedure of running a "control" group in parallel with the "experimental" group.

Note: $\hat{x}_i$ has again been neglected for clarity; inclusion would simply require the Monte Carlo and hillclimbing procedures to be performed in two dimensions.

The advantages of this algorithm are:

1. Use of the Monte Carlo procedure allows the algorithm to adapt to a slowly changing environment, and prevents repetitive cycling in that "new" trajectory possibilities are selected in proportion to their cost probability.
2. The procedure 1 to 6 can be repeated several times, selection of the final trajectory being made on actual cost. This would result in more rapid probability distribution "learning" and a superior final trajectory.
3. In an extreme case the mappings B and C (and thus the inverse mapping B^{-1}) need not be performed, the algorithm working directly in 2n dimensional $u_1, u_2, \ldots\ldots u_n, x_1, \ldots\ldots, x_n$ space. Note that in this case the computation per interval (for a discrimination of r) involves r^{2n} Monte Carlo evaluations and one 2n

dimensional static optimization, approximately the same as the normal dynamic programming solution. Various possibilities between full B and C mappings (requiring r^2 Monte Carlo selections, one 2n dimensional and one n dimensional static optimisation per interval) can be chosen to suit the particular problem and the particular computational limits.

The proposed algorithm has not been tested, however some preliminary investigation of the mapping procedure has been carried out. For the initial investigation of the Tasman system, the mappings B and C were not necessary as: 1) the state variable X was neglected, and 2) the single control variable was taken as ΔX over the interval. For this system the critical feature of the loading set for any interval is the total electrical loading, this directly influencing groundwood manufacturing capability. Consequently, initial attempts to form a composite single valued interval loading reflecting "stress" on the system, involved conversion of all system interval loadings into a composite electrical load.

Composite Electrical load (t) =

$$CEL(t) = a_1 y_1(t) + a_2 y_2(t) + \dots \; a_7 y_7(t) \qquad \text{4.13}$$

where: (1) a_i are conversion coefficients

(2) $a_3 = 1$

<u>Table 4.1 Composite Load Conversion Coefficients</u>

1 lb 650 psi clean steam	0.10 KWH Elect.
1 lb 150 psi clean steam	0.08 KWH Elect.
1 lb 50 psi clean steam	0.05 KWH Elect.
1 lb 220 psi geothermal steam	0.043 KWH Elect.
1 lb 100 psi geothermal steam	0.04 KWH Elect.
1 ton groundwood pulp	1,200 KWH Elect.
1 ton finished paper	2,595 KWH Elect.

Table 4.2 Composite Electrical Load (CEL) for Period 9, 1968

Day	CEL	Day	CEL	Day	CEL
1	1688	12	2209	23	1939
2	2133	13	2146	24	2018
3	2132	14	1978	25	1922
4	1974	15	1439	26	2075
5	1968	16	1039	27	2131
6	1878	17	1701	28	2112
7	1901	18	1947	29	2121
8	2146	19	2100	30	2126
9	2187	20	1928	31	2142
10	2229	21	1990	32	2186
11	2182	22	1830		

For the limited investigation performed, the values of $a_i, \forall_{i \neq 3}$ were chosen from suitable averages of the model transfer coefficients (see 2.4.3.). Resultant values are given in Table 4.1, hence the values of CEL for Period 9, 1968 given in Table 4.2.

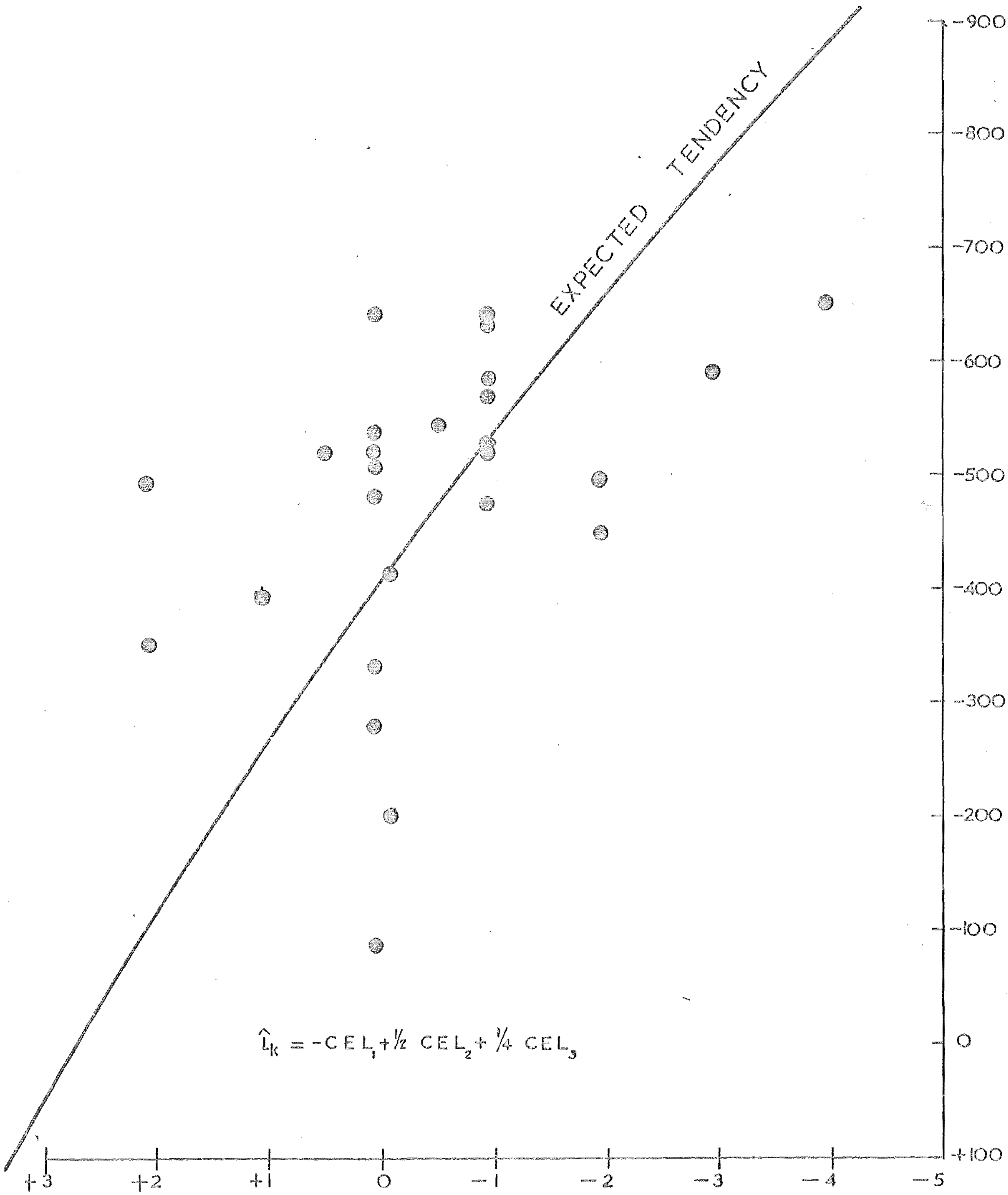
The values of $\hat{1}_k$ were formed as a linear function of the composite electrical loads of the k intervals in the planning horizon:

$$\hat{1}_k = b_1 \, CEL_1 + b_2 \, CEL_2 + \ldots\ldots + b_k \, CEL_k \qquad \ldots\ldots \quad 3.14$$

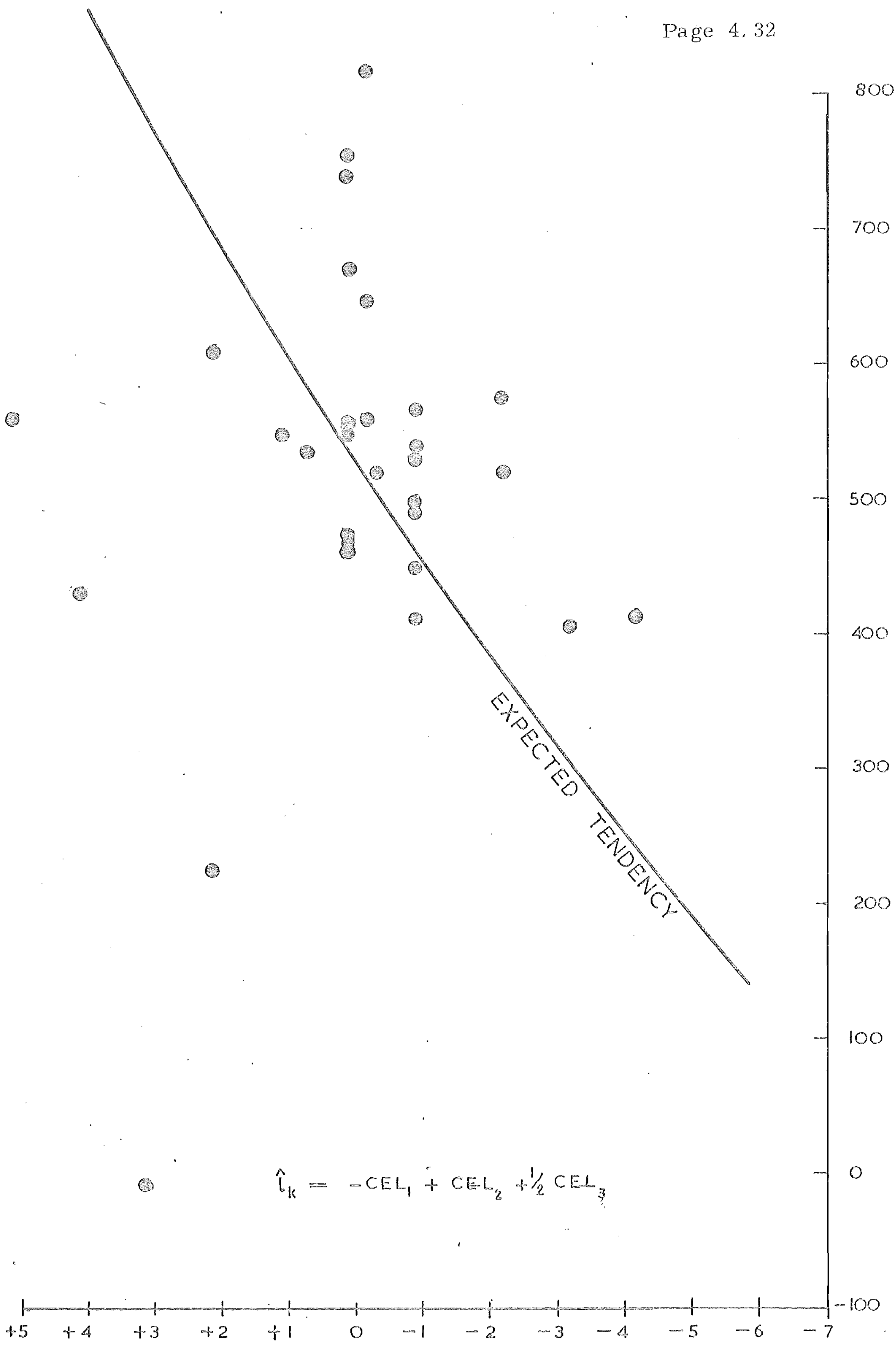
Weighting of the b coefficients, $b_i > b_{i+1}$, results in a discounting of the effects of more remote intervals.

For preliminary investigations a three interval planning horizon was used, choice of the b coefficients being rather arbitrary. High values of the CEL for the immediate first interval i require the optimal action to utilize stored energy, hence in both cases shown (Graphs 4.1 and 4.2) b_1 is negative. High CEL in intervals i + 1, i + 2, ... require that potential energy be stored, hence b_2, b_3, ... are positive. Graphs 4.1 and 4.2 show plots of $\hat{1}_k$ against optimal action as determined by the off-line Dynostat program for Period 9, 1968.

While these results are not very significant they do reveal some tendency in expected direction as shown, encouraging future work with this proposed algorithm. A more suitable form of testing would



GRAPH 4·1 PLOT OF $\hat{l}_k$ VS. OPTIMAL ACTION ΔX



GRAPH 4.2 PLOT OF $\hat{l}_k$ VS. OPTIMAL ACTION ΔX

involve regression analysis choice of the parameters a and b, however this would involve more data than was available during the course of this study.

It is interesting to note that this proposed algorithm is of the extended static form, similar to those discussed in 3.4.2. The predictive or "look ahead" capability here is based on a heuristic cost or "future stress" relationship rather than a deterministic relationship as before. The wheel has turned through a full circle, the major difference in approach being the manner in which the effect of the future on present strategy is assessed.

A promising alternative heuristic approach to the dimensionality problem of dynamic programming is that developed by Hart et al (3). Their A* algorithm was developed for the problem of finding a minimum cost path through a general graph or network, and so lends itself for adaption to the "standard" dynamic programming problem. The evaluation function is taken as $f(n) = g(n) + h(n)$ .... 4.15 where $g(n)$ is the cost of the most optimal path so far found by the algorithm from the initial node to node n; and $h(n)$ is a lower bound estimate of the cost of the optimal path from node n to the goal node. At each step in the algorithm the node with minimum $f(n)$ is expanded. When no information is available on $h(n)$, $h(n)$ is taken as zero, with the result that every node is expanded as in dynamic programming. Generally, the number of nodes expanded is a function of the amount of information available on $h(n)$. Obviously, such an algorithm could be utilized in conjunction with the Dynostat approach to reduce the computation required; the reduction depending on the accuracy of future cost estimation for the particular problem.

4.3 SYNTHESIS OF SENSITIVITY ANALYSIS ALGORITHMS FOR THE OPTIMUM SCHEDULING PROBLEM

For problems involving static optimisation, analysis of the sensitivity of optimal solutions produced is comparatively simple. Cost sensitivity, or the sensitivity of the optimal functional value to small changes in any input variable, can be simply considered as the peakness of the response surface in the region of the solution (4). A measure of this peakness can be readily obtained by perturbation analysis about the optimal point. Similarly, restraint sensitivity or the likelihood of the optimal action producing a forbidden or restrained situation due to possible changes in input variables can be considered as the state space distance between the optimal point and the nearest restraint boundary. This may also be assessed by a suitable perturbation study. The latter type of sensitivity only applies to certain types of system, for example, a boiler operated within rigid pollution limits.

The possible variations of input variables can be described by probability distributions: by relating the distributions to cost sensitivity, probabilities may be assigned to cost ranges; by relating them to constraint sensitivity the probabilities of undesirable (or otherwise) occurrences may be assessed.

In contrast, the sensitivity of dynamic trajectories is not at all easy to visualize owing to the multitude of possible input variable combinations over time. Even with systems of low dimension analytic techniques are intractable (5), so recourse must be made to numerical computer techniques.

The problem does not appear to have received intensive study in the literature. Stage and Larsson (6) refer to constraint sensitivity in defining a minimum or forbidden zone in trajectory space, however no details are given apart from a statistical definition. Other authors (7, 8) define a similar zone by computing the boundary trajectory which just fails to run storage completely empty, given that the inflow for each month is the least ever recorded. Cost sensitivity is not referred to at all, however this is partly taken care of where stochastic optimisation techniques have been used: e.g., stochastic dynamic programming as in (9, 10, 11), or the cost weighting methods of (12, 13). Use of these techniques gives the trajectory with minimum expected cost, however they do not yield any actual information on the range of cost likely to be encountered in practical application.

In the course of this study simulation techniques for evaluating trajectory sensitivity for varying conditions and assumptions on the decision processes have been evolved. These are discussed in chronological order.

4.3.1. Sensitivity of Purely Off-line Trajectories

Given the situation were precomputed optimum trajectories are applied to the system direct, with no correction for unexpected occurrences, the cost and constraint sensitivities are relatively easy to obtain. Simulation of system performance for given disturbance and control sequences gives system response to input schedules. Selection of disturbance sequences can be achieved by Monte Carlo methods based on disturbance probability distributions. (14).

By repeating the system simulation for each disturbance sequence, and holding the control sequence fixed equal to the optimum schedule, the constraint sensitivity probability and cost sensitivity probability distributions may be directly obtained.

Such a procedure is unfortunately not applicable to this study as:

a) the effects of the often significant deviations of disturbance values from those expected are cumulative, hence constraints are usually broken with a few intervals (i.e. constraint sensitivity probabilities are very high),

b) to alleviate the effects of unexpected disturbances an on-line decision making process has been formulated. The direct sensitivity study as above makes no allowance for the effects of this unit.

4.3.2. Sensitivity of Trajectories Allowing Total Off-Line Recalculation

This approach assumes that all deviations in the disturbance values taken for the initial off-line optimisation, become known before the real time application of the schedules. Hence a full recalculation is possible.

The obvious way of obtaining both cost and constraint sensitivity information on the original schedule is to continually simulate loading sequences over the time horizon of the schedule, and perform a separate optimization for each sequence so produced. Repeated performance of this procedure would permit a probability distribution for optimal cost to be plotted, and assessment of the likelihood of an enforced shut down of an output production unit, for particular ranges of input disturbance values.

This full approach however is impractical owing to the extremely large computation requirement for even reasonably accurate probabilities and distributions.

Table 4.3 Preliminary Sensitivity Studies

Description of loading	Enforced reduction in system output	Variation in energy cost over planning horizon
Original optimum schedule (MD=46.2MW)	NO	-
Alternate ± 10% on 150 psi clean steam MBL	NO	- 0.04%
" ± 20% " " " " " "	NO	- 0.07%
" ± 50% " geothermal steam MBL	NO	+ 0.11%
" ± 10% " 50 psi clean steam MBL	NO	- 0.03%
" ± 50% " " " " " "	NO	- 0.03%
" ± 10% " electrical MBL	NO	- 0.05%
" ± 10% " total paper machine prod.	NO	- 0.13%
" ± 15% " " " " "	YES	-
+ 10% on electrical MBL	NO	1.34%
+ 10% on total paper machine production	YES	-
3% reduction in groundwood manufacture capability	YES	-
Alternate ± 10% on electrical MCL using optimal trajectories and constraints corresponding to MD = 35 MW	YES	-

Initially, an abbreviated form of this approach was used to obtain some idea of the trajectory sensitivity. The particular optimum trajectory tested was that obtained by the off-line Dynostat program for Period 9, 1968, with MD = 46.2 MW. Instead of using a Monte Carlo simulation of disturbance sequences, which would require many program runs for meaningful results, runs were performed varying only one system loading from its expected values over the planning horizon (generally an alternate $\pm$ % of interval loading). The results of these preliminary investigations are shown in Table 4.3.

As would be expected, the results of this study are extremely limited in application, however they do serve to show up the sensitive sections of the process e.g. the groundwood section, where even a 3% reduction in capability is sufficient to cause a system output reduction.

4.3.3. Sensitivity of Trajectories Allowing Constraint Sensitive On-line Correction

In the previous sections it was assumed that all disturbance deviations from expected values were known before the real time application of the optimum schedules. In practice, although some deviations may become known beforehand, this assumption is not generally valid. The more probable situation is that disturbance deviations become known as they occur, or with very short lead time. This corresponds to the on-line updating situation.

Given the likely situation where an on-line computer is not available, optimum schedules will be supplied to a human operator. Although this operator will be able to utilise intuition and understanding of the problem to minimise operational costs, the primary responsibility will be to ensure that shortages of energy or intermediate products do not cause a loss of system output. Constraint sensitivity therefore, is of paramount importance (the nett cost of any loss of production far exceeds energy cost perturbations which may occur). A method for determination of the constraint sensitivity of the original schedule in this environment has been developed (15).

The operations schedules produced consist of an N-stage trajectory in the major system intermediate product storage level (N-discrete intervals in the period of interest), and the corresponding optimum values of the system control variables for each stage with respect to the expected system loadings. The off-line optimal assessment may be considered as committing the system to the expected optimal trajectory - this being achieved (in the absence of non-expected loading) by manipulation of the appropriate control variables to the predetermined values of the optimal schedule assessment.

Now in any physical system three types of constraint may exist as follows:

1. physical constraints, e. g., equipment saturation levels,
2. equilibrium constraints e. g., Supply = Demand,
3. storage constraints, e. g., Minimum $\leqslant$ Storage Level $\leqslant$ Maximum.

Consider all product flows within the system as flows of 'equivalent energy'. Now if the predetermined schedules are followed (i. e., no corrective action), then physical and equilibrium constraints are satisfied, and deviations of actual loadings from the expected loadings will cause the actual trajectory to diverge from the expected optimum, until in the limit the storage constraints are broken. Whether the upper or lower constraint is broken is dependent on the form and magnitude of the sequential sets of loading deviations - two extreme cases are illustrated in Figure 4. 15.

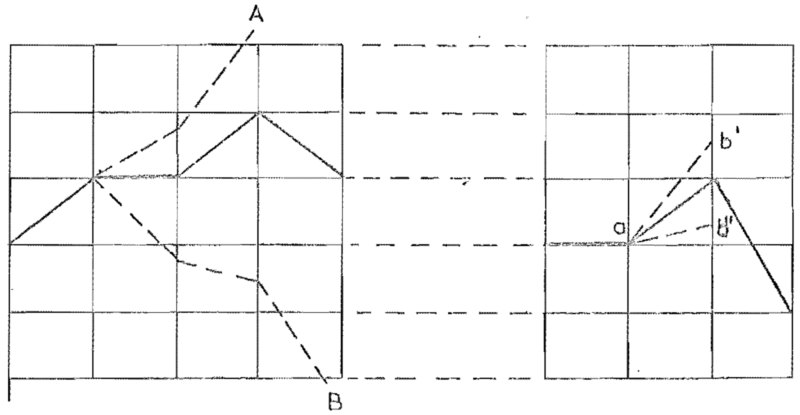


FIG. 4·15 SCHEMATIC OF AN OPTIMUM ROUTE SHOWING THE TWO POSSIBLE EFFECTS OF NON-EXPECTED LOADINGS

It may be seen that corrective action employing the control variables can always prevent deviations such as A by reducing the input of 'equivalent energy' to storage, however limitations on the supply of 'equivalent energy' (physical and equilibrium constraints) restrict corrective action in prevention of type B deviations. Thus the constraint sensitivity may be expressed in terms of the probability of deviations such as B occurring in the presence of all possible corrective actions, i.e., the probability of the system being unable to satisfy production demands.

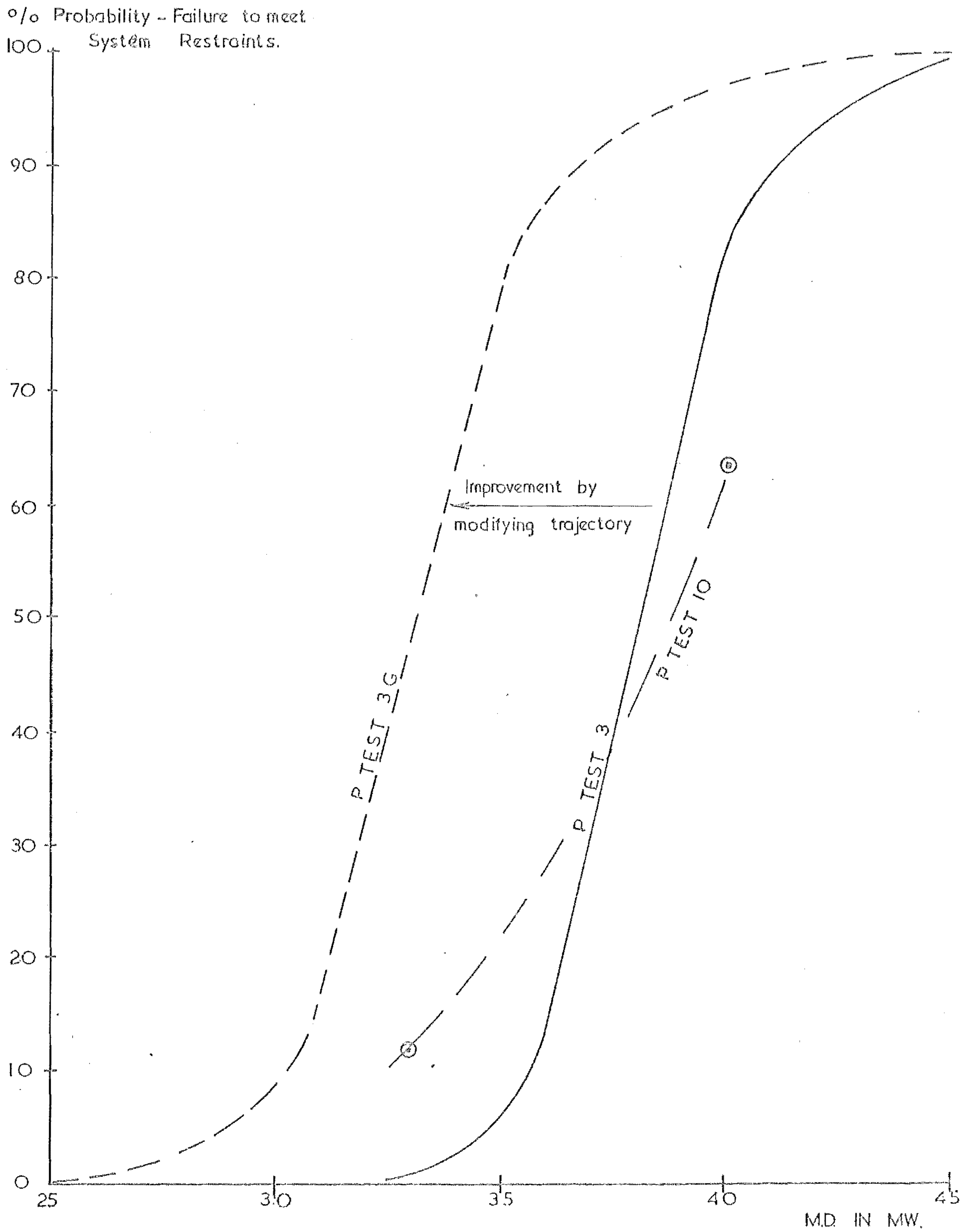
A program was produced which determines the probability of this enforced reduction in output, given a particular storage trajectory and the values of the associated system parameters. This program uses the Monte Carlo technique in the following fashion: At any grid point, a, on the particular route, all system coefficient and loading values for the next interval are selected from their cumulative probability distributions by means of a random number generator. Given these loadings, the maximum possible storage input for the interval is computed (with respect to constraints 1 and 2), this giving the maximum storage level attainable at the beginning of the next interval. If this level is greater than that required to remain on the particular trajectory (e.g., point b' - Figure 4.15) then for the next interval the initial level is taken as b. If however, the maximum level attainable is below that required to remain on the particular route (e.g., point b''), then for the next interval the initial level is taken as b''.

This procedure is carried out for all intervals in sequence - if for any interval the maximum attainable level is below the minimum allowable level, this is regarded as a failure.

If many runs are carried out, then the probability of a production loss for a particular route is given by P, where;

$$P = (\text{number of failures})/(\text{total number of runs}). \quad \ldots\ldots \quad 4.16$$

The sensitivity of the various trajectories can thus be assessed.



GRAPH 4·3 PLOT OF CONSTRAINT SENSITIVITY V.S. TRAJECTORIES FOR VARIOUS MAX. DEMANDS.

A series of similar programs each using a slightly different model (see Chapter 2) was developed in an evolutionary fashion. The program PTEST3 was the most general of these, in the sense of having all variables described by probability distributions and participating in the Monte Carlo process, rather than having some variables described by probability distributions and the remainder holding to the deterministic loading schedule. Constraint sensitivities of the optimum trajectories obtained (using the off-line DYNOSTAT program) for various values of maximum demand are shown in Graph 4.3. The maximum improvement possible by modification of these trajectories is also plotted, this being obtained using a policy of maximising storage levels at all times.

Although not performed in this study, actual operation cost data could readily be obtained by totalling the cost response of the system over each interval, including the effects of any operator interaction. The cost sensitivity distribution for the original trajectory could thus be assessed. The accuracy of the distribution obtained in this manner however is open to question as operator response is highly variable in this context, and may differ considerably from any programmed subjective assumptions.

4.3.4. Sensitivity of Trajectories with Full On-line Optimisation

Given the availability of a suitable computer the on-line Dynostat can be utilized to optimally update the original schedules in the light of the latest available information on the system. In this case cost and constraint sensitivities for both the original and updated trajectories may again be obtained by simulation of the system behaviour and the corresponding decision making process.

Consider the computing scheme as shown in Figure 4.16. This scheme simulates the real time behaviour of the system and the controller: at interval i the system loading values are selected randomly from the appropriate probability distributions, and the on-line algorithm takes the appropriate optimum control action over the interval. This action results in the optimum system state at the beginning of the next interval, wh ere the procedure is repeated.

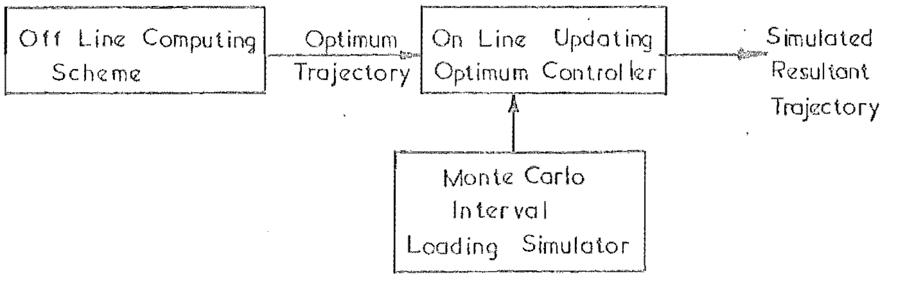


FIG 4.16 COMPUTING SCHEME TO DETERMINE COST & CONSTRAINT SENSITIVITY

Traversing this procedure across the planning horizon of the trajectory many times results in a probability value for constraint sensitivity, and a distribution of actual operational costs.

Instead of terminating a particular traverse when the value of the state variable (storage level) is forced below a certain minimum value, it is possible to continue the procedure whilst holding the demands serviced by this variable at zero (i.e., shutdown of paper machines). When the variable again assumes a permitted value the particular demands would be allowed to take on unrestricted values as before. Thus a normal simulation would not only give a cost distribution and a constraint sensitivity probability, but also a downtime or "time of constraint dissatisfaction" probability distribution. For the period that the paper machines are shut down the system suffers a loss of revenue given by the loss of production times the selling price of the product. Loss of production is given by the sum of the output unit loadings which would have occurred over the period when unit demands were artificially supressed. Hence a loss of production or loss of revenue probability distribution may also be plotted.

Equating probable loss of revenue with possible decrease in energy cost allows realistic comparison of trajectories for minimum overall cost.

4.3.5. Composite Sensitivity/Security-Dynamic Optimisation Algorithm

It is proposed that the Dynostat optimizing algorithm be combined with a sensitivity routine to yield optimum trajectories in terms of both overall energy cost and sensitivity. The particular sensitivity routine used depends on the form of the loading distributions available, and the security (or inverse sensitivity) requirements.

Consider the simplest case, where the loading distributions are identical for each interval of the schedule planning horizon, and where the resultant trajectory is only required never to exceed a certain probability of constraint dissatisfaction. For the single dimension state space grid of Figure 4.17, if the loading distributions are stationary over the planning horizon, then the constraint security of a trajectory is limited by the lowest grid point passed through, regardless of the time of this occurrence. Hence each grid level may be assigned a security

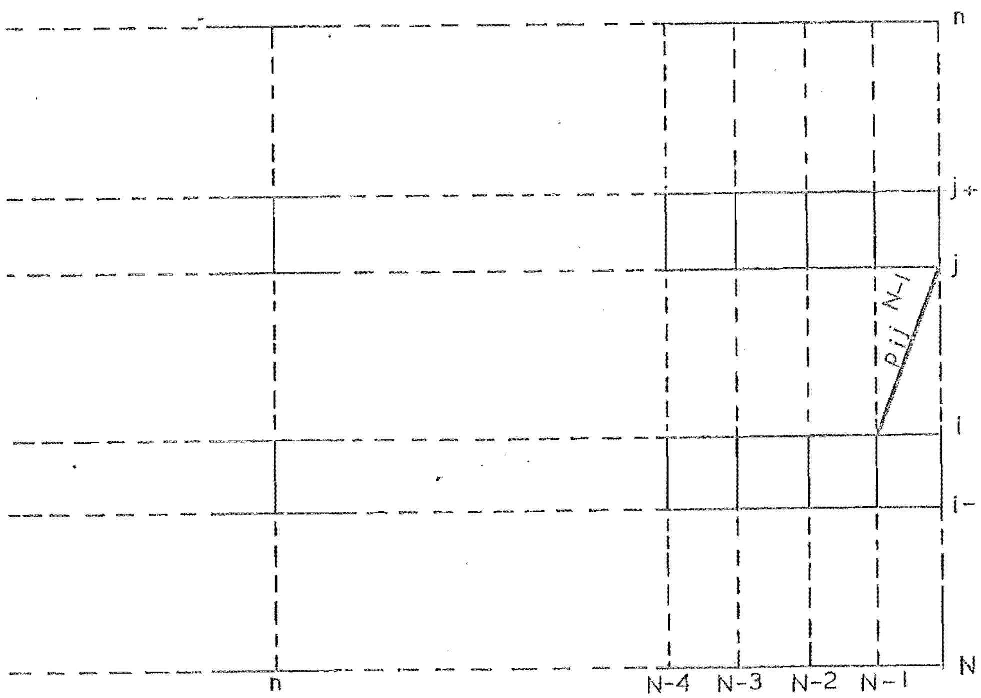


FIG. 4·17 STATE SPACE GRID

(or sensitivity) value which can simply be determined by use of the simulation program of 4. 3. 3. operating on a constant level trajectory.

The combined program thus has the following major steps:

1. Determine the security value of each allowable level of state variable.
2. Connect up the grid points having security values equal to the given minimum allowable security value. This forms the new lower state variable constraint.
3. Proceed to compute the expected optimum route using the Dynostat program.

For cases where the distributions are non-stationary, but where it is necessary to impose the same limits on allowable trajectories, a similar method may be used, however it will be necessary to perform a more complex analysis to determine the security values of each grid point. For the nth grid intersect of Figure 4. 17, let p_{ij}^{n} be the probability that the maximum possible groundwood production increases the storage from node (n, i) to (n + 1, j), where i and j denote the ith and jth discrete storage levels. For any intersect repetitive Monte Carlo simulation can establish these probabilities; alternatively analytic methods may be used. (Note: Cases which exceed the maximum allowable storage level are included in the upper node probability value).

Consider the node (N - 1, i). The probability that a trajectory, having reached this node, can terminate at a level above the minimum constraint is given by $P_i^{N-1} = \sum_{j=1}^{r} P_{ij}^{N-1}$. A value of P_i^{N-1} can be determined for each of the r grid levels. This value is the security value of the particular node. Taking now the (N - 2)th node, the success or security probability of the ith node, is given by:

$$P_i^{N-2} \text{ (sec)} = \sum_{j=1}^{r} P_{ij}^{N-2} * P_j^{N-1} = \sum_{j=1}^{r} P_{ij}^{N-2} \sum_{k=1}^{r} P_{jk}^{N-1} \qquad \ldots\ldots\ldots\ 4.17$$

Hence a security value can be assigned to each of the r nodes of intersect N-2.

Repeating the procedure sequentially back to the 1st intersect of the planning horizon gives a security value to each node of the grid. The similarity to the Dynamic Programming procedure is immediately obvious.

By connecting up grid points having security values equal to a given lower limit, a new lower storage constraint can be defined. A Dynostat computation as above then determines the expected optimum trajectory.

If, instead of using the simulation techniques of 4.3.3. to determine security probabilities, the method of 4.3.4. is used, a small modification directly provides a powerful stochastic optimization tool with a built-in sensitivity analysis. Define a desired end point or trajectory boundary point on intersect N. For each node of the (N-1)th grid intersect, a probability P_i^{N-1} of attaining the end point (or alternatively a probability of not breaking a system constraint and causing a production loss), and a probability distribution function for optimal cost $P_i(C)$ of the incremental trajectory may be established by either Monte Carlo analysis or analytic techniques. Similarly, for each node of the (N-2)th intersect, security probabilities P_{ij}^{N-2} and cost distribution functions P_{ij}^{N-2} (C) for the transition from that node to each of the r nodes of the (N-1)th intersect can be determined.

Consider the node (N-2, i). The probability of attaining the end point (goal satisfaction) is given as before by equation 4.17. Using derived distribution techniques (16), the distribution functions P_{ij}^{N-2} (C) and P_j^{N-1} (C) may be combined to yield the distribution function for the trajectory connecting the nodes (N-2, i), (N-1, j), (N, e). Using some constant basis of evaluation, cost distribution functions for the permitted trajectories having end points (N-2, i) and (N, e) may be compared to select the optimum. Only those nodes having suitably high probabilities of goal satisfaction are considered. The optimum trajectories for each value of i can thus be determined. Repeating the procedure for the (N-3)th, (N-4)th ...., 1st interval isolates the overall optimum trajectory.

The schedule obtained by this method is:

1) optimal with respect to probabilistic and deterministic disturbances (in an off-line case), and;

2) has a probability of goal satisfaction (alternatively security probability) which is above some stipulated value. This algorithm therefore fulfills the requirement for a combined stochastic optimisation and sensitivity analysis.

The latter two algorithms of this section (i.e., the On-line Reoptimisation procedure of 4.3.4. and the Composite Algorithm of 4.3.5.) would appear to hold considerable promise. Future research is intended to evaluate the operational performance of the concepts involved.

4.4 SUMMARY

In Chapter 2 the overall problem was decomposed into a hierarchical structure of subroutines. Broad specifications for the algorithms to solve the subproblems were drawn up, resulting in the algorithmic hierarchy of Figure 2.12. Chapter 3 described the application of established technique to suitable subproblems of this structure. In this chapter the development of new techniques to solve the remaining subproblems has been presented, and may be summarised as follows:

The primary area of development effort has been the intermediate term optimal scheduling problem. The fundamental breakthrough in the development of an optimisation method was the derivation of the Dynostat concept: combining dynamic and static optimisation methods. Although this concept arose through the approach of utilizing specific features of the problem, it is considered to have a considerable breadth of application, and is reported on in (17).

Following development of the basic off-line Dynostat algorithm, the specific requirements of the on-line optimisation problem were examined. Analysis and restatement of the "Principle of Optimality" lead to the concepts of an on-line dynamic method. Development of these concepts resulted in the on-line dynamic optimisation program presented in 4.2.2.4. Although the basic calculation involved in this

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CHAPTER 5 A PROPOSAL FOR IMPLEMENTATION OF THE ENERGY OPTIMISATION TECHNIQUES

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INDEX OF ILLUSTRATIONS

CHAPTER 5 A PROPOSAL FOR THE PLANNED INTRODUCTION OF ENERGY OPTIMISATION TECHNIQUES TO THE INDUSTRY

5.1 INTRODUCTION

This thesis is concerned with energy optimisation in an existing industrial system. There are three major facets to any such task which are of interest within the timescale of the study (1):

(a) System Analysis, involving decomposition of the problem into a set of manageable subproblems and the evolution of a suitable system model.

(b) System Synthesis, involving the development of suitable techniques and algorithms to solve the subproblems determined in the analysis phase.

(c) Implementation of the techniques and algorithms of the synthesis phase in the industrial environment to provide optimum control

The analysis and synthesis phases of the study have been presented in Chapter 2, and Chapters 3 and 4, respectively. Although full implementation of the techniques and algorithms developed is outside the scope and timescale of this academic study, the thesis would not be complete without a plan for this implementation. In this chapter an implementation philosophy and a plan for the introduction of both the particular methods developed and general systems engineering technique are presented.

Whereas the time scale for the introduction of the new techniques is ill-defined due to uncertainties of technical data, management policy and other matters outside the control of the student, nevertheless the proposed plan is a serious attempt to set in motion events which will ultimately lead to implementation of the new ideas at the plant.

5.2 A PHILOSOPHY FOR THE INTRODUCTION OF NEW TECHNIQUES

One of the original objectives in the initiation of this study was the mutual benefit to be obtained from an increase in University/Industry cooperation. This benefit stems directly from the differences in engineering objectives of the two organizations, the firm being more concerned with matters of detail and application, and the University with matters of principle and general technique. Throughout the organization of this study and in particular in the derivation of a plan for implementation the distinct objectives of each group have been recognized. In this way it is believed firstly that the overall efficiency of the approach benefits and secondly, that the basis for a continuing post doctoral relationship between the firm and the University is established.

The field of Systems Engineering with its computer oriented techniques is assuming increasing relevance to the industrial situation - the function of a University in the development of these new techniques makes such a University/Industry project an ideal vehicle for the introduction of the new technology to the industrial environment.

As pointed out by Church (2), sudden 'step' changes in technology can have disastrous consequences. This form of introduction has frequently resulted in projects being started without adequate preparatory investigation and justification: Equipment is purchased which is not best suited to the job, and long and expensive delays in achieving satisfactory on-line performance through poor understanding of the concepts or equipment involved can occur.

The second major part in implementation philosophy proposed here is that implementation should be gradual: viz. in the form of a "ramp" function - versus time characteristic, roughly the inverse of the classical human operator learning curve. This involves a progressive introduction of new technique through the acquisition of system data and the testing of the methods and techniques developed in the University study, through to the progressive implementation of discrete sections of the project. In this manner suitable experience will be acquired over a period of time to ensure satisfactory completion of each step in the progressive implementation, each step will be thoroughly tested and proved before implementation, and the progressive approach will give increased operator confidence.

The overall project concept can be concisely expressed:

(1) development of general methods and techniques suitable for implementation by the student at the University,

(2) transfer of this methodology to the firm by the student joining a Systems Group at the firm on completion of the study

(3) the acquisition of system data, and the testing of models and techniques in the industrial environment, and

(4) the progressive implementation of proven sections of the project. Study effort is thus transferred from the University to the firm, with the University providing a backup only on matters of principle.

5.3 A PLAN FOR THE IMPLEMENTATION OF THE ENERGY OPTIMISATION TECHNIQUES

The proposed parallel working arrangement between the University and Industry groups is shown in Figure 5.1. Note the gradual introduction of the "systems approach" to the industrial environment. To avoid a conflict between the academic requirements of the University and the 'detail' requirements of the firm, each group has specialist objectives that make up the broad study necessary for success.

5.3.1. The University Group

This group should consider the class of problems to which the particular problem belongs, proceeding to acquire and to add to comtempory knowledge in that field. Testing and proving of technique should utilise the particular problem - thus work usefully related to the industrial project is achieved without prejudicing the quality of the academic study.

The schematics of Figures 5.2, 5.3 and 5.4 indicate the content of the three studies within the planning horizon. Although three full time studies are shown, only the first is primarily concerned with the energy optimization project. The remainder are involved with the project but in more of a 'back-up' sense than total commitment.

5.3.2. The Industry Group

The Systems Engineering Group proposed (3), should be relatively independent of normal production activities of the firm, and should carry out research into broad systems engineering problems affecting the firm's operations: particular attention being paid to the application of computer oriented control.

In addition to the power optimisation project and any other possible computer control applications, this group should determine and study new techniques with potential value to the Tasman Company. It should be responsible for the introduction and preliminary systems analysis, synthesis, and cost benefit studies of systems projects. If implementation is warranted, specific project teams would be formed as recommended by Jenkins (1) - these would contain specialists from the various departments involved.

The schematic of Figure 5.5 indicates the first four year programme for the proposed group. There are three distinct sections to this plan:

1. Data Acquisition and Handling - Recordings of plant performance and behaviour will initially be performed manually, although this function will ultimately be automated in any on-line computer system installed. This section also covers the forecasting of aspects of plant behaviour as required, and providing systems data for models.
2. Power Optimisation Project - This consists largely of detailed testing and cost benefit studies.
3. Studies of Related Applications - Investigations of data logging and production unit automatic and computer control are envisaged.

5.4 SUMMARY

This chapter has briefly outlined a philosophy for practical application of the results of this study. Although tentative and cautious in its recommendations, it does propose positive steps and approaches to the practical implementation problem. Definite action to be taken to initiate the next step in the implementation strategy can be based on it. The ideal Industry - University liaison proposed should benefit both Industry and University interests.

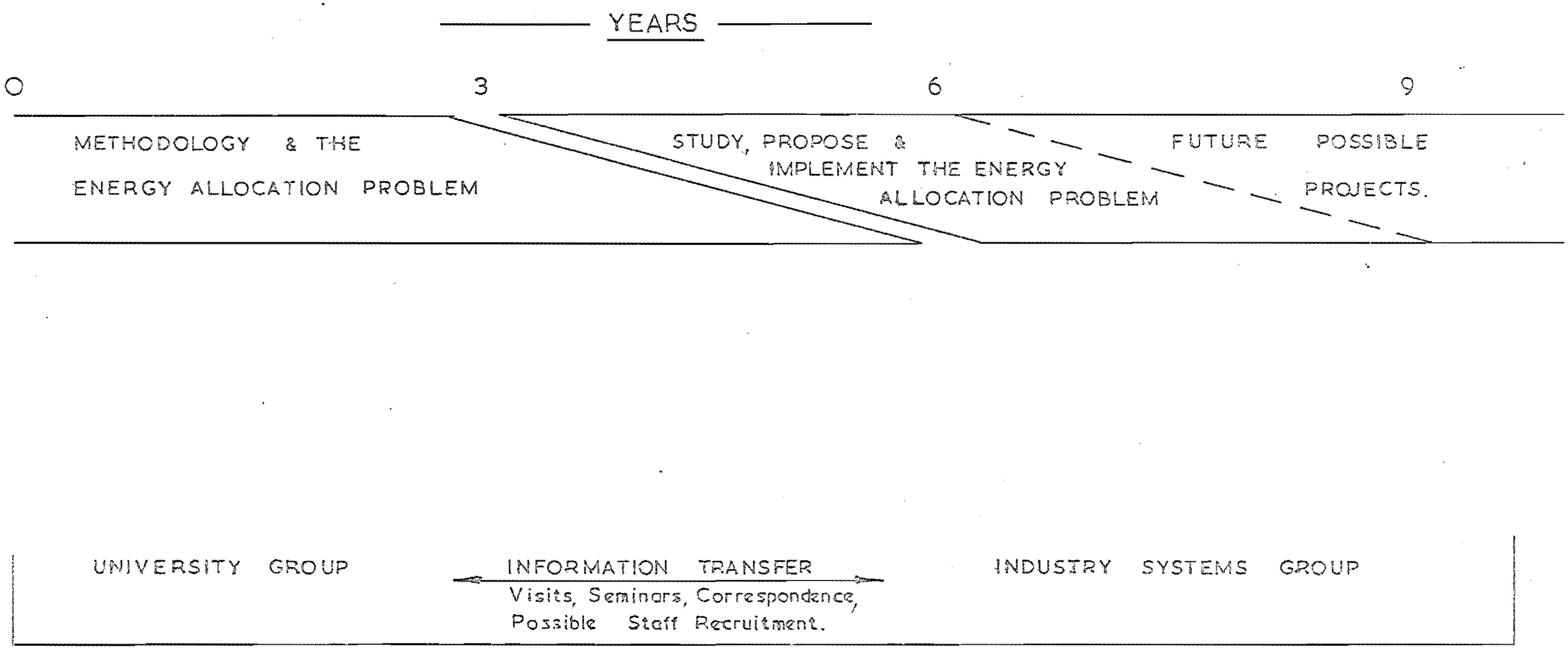

FIG. 5·1 THE JOINT STUDY PLAN.

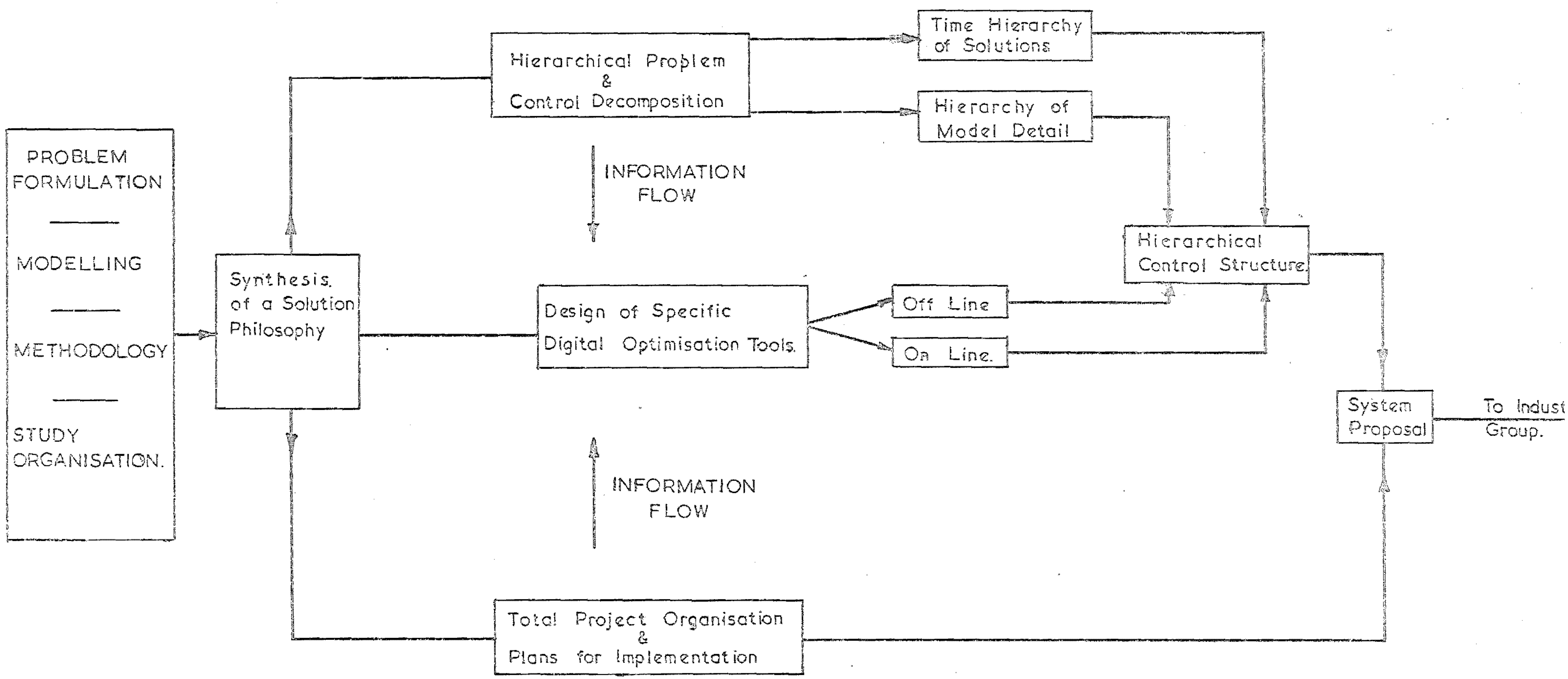

FIG. 5.2 THE UNIVERSITY SYSTEMS STUDY.

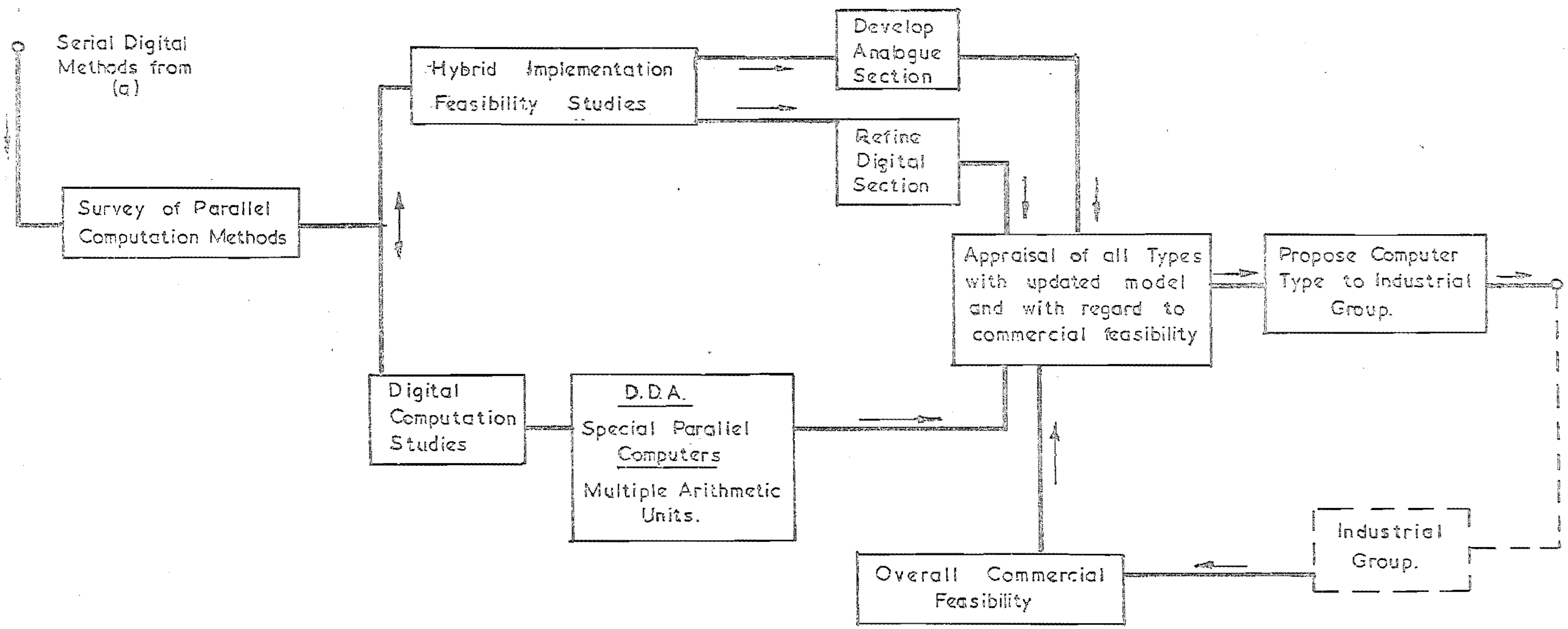

FIG. 5.3 THE UNIVERSITY COMPUTER METHODS STUDY.

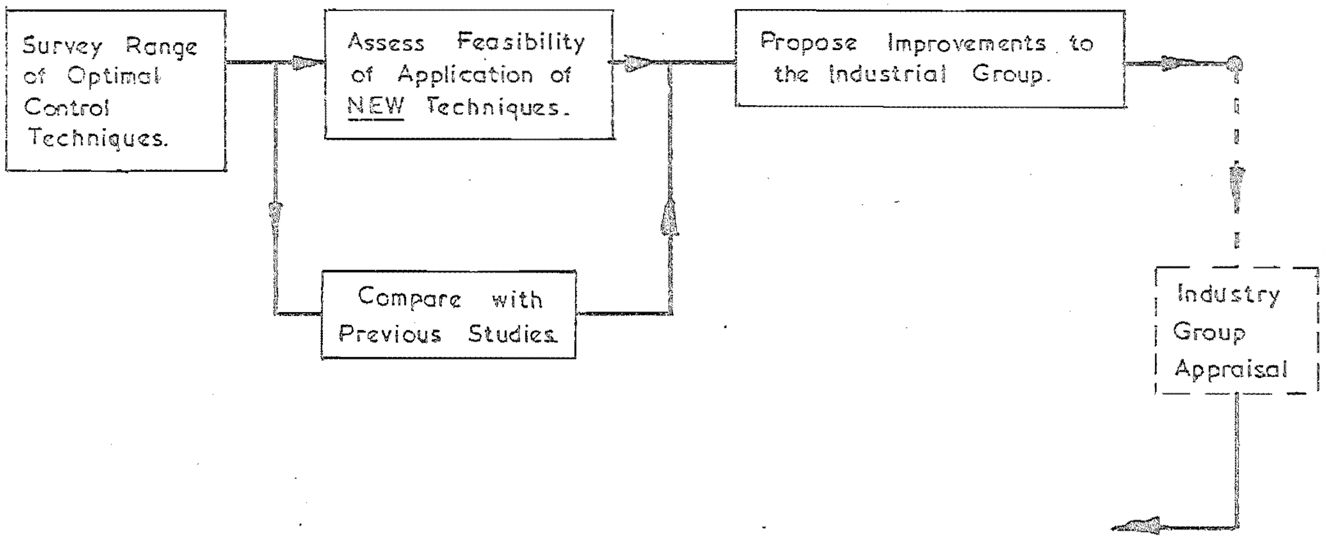

FIG. 5·4 THE UNIVERSITY ADVANCED METHODS STUDY.

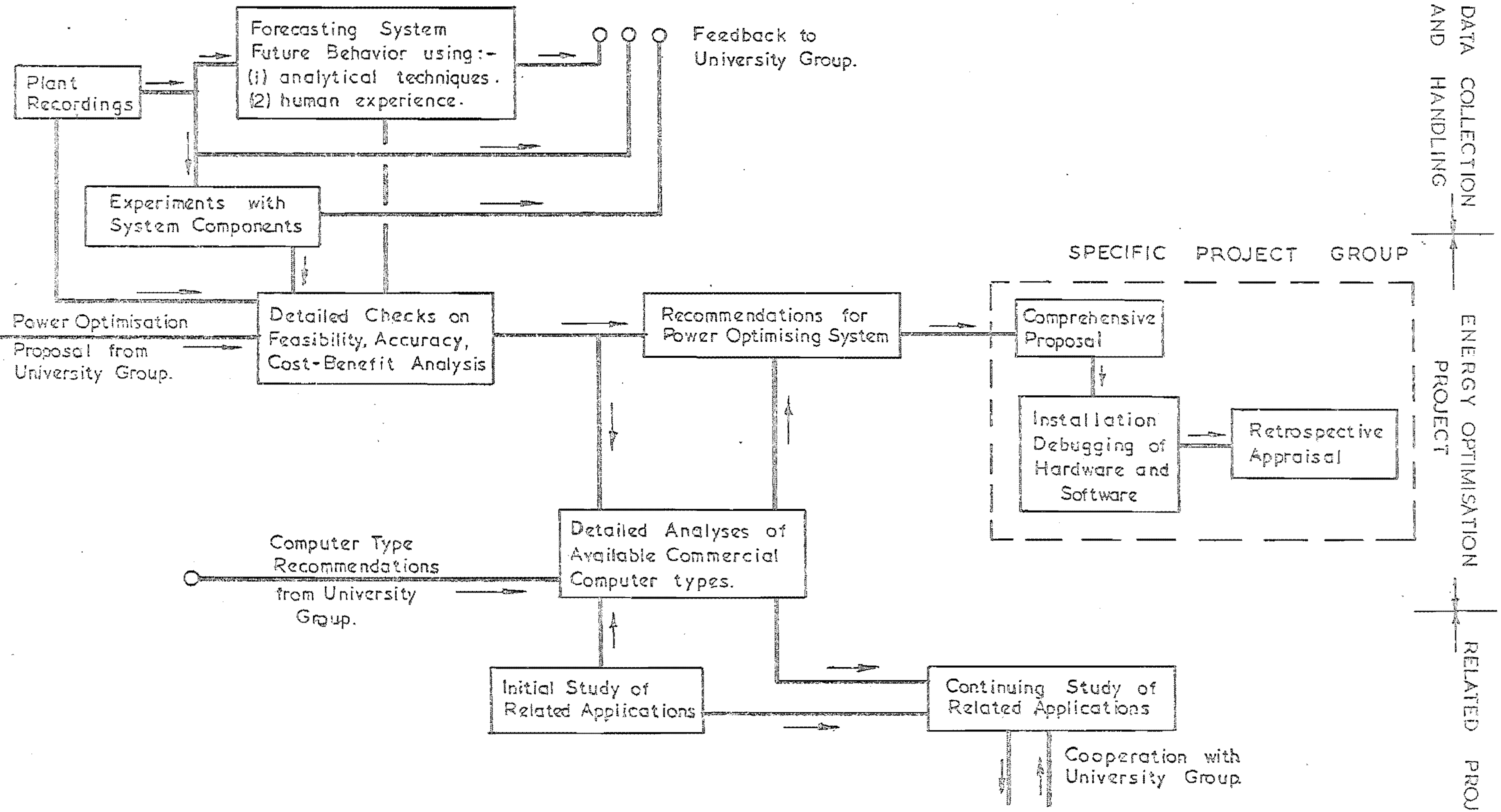

FIG. 5.5 INDUSTRY GROUP IMPLEMENTATION PLAN.

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CHAPTER 6 SUMMARY AND DOCUMENTATION OF THE THESIS

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CHAPTER 6 SUMMARY AND DOCUMENTATION OF THE THESIS

6.1 INTRODUCTION

This thesis has presented the author's contribution to the problem of energy optimisation and to an appreciation of the future role of optimum control, at the Tasman Mill. The primary emphasis has been on the technical aspects of the work, in sufficient detail to form the foundation for the next stage towards practical implementation. The other important aspects such as selection and initiation of the study, organisation of the project, and planning for implementation have also been mentioned.

Although much more work on practical details is required for full implementation, the major theoretical problems have been solved and a framework for the co-ordination of future optimisation problems has been established.

The aim of this chapter is to summarise the thesis by presentation of the contributions to the state of the art, contributions to the industry, other documentation of the work carried out, and areas of potentially valuable future research.

6.2 CONTRIBUTIONS OF THE THESIS

The breadth of scope of the Systems Engineering research of this study has spread the contributions to the state of the art over a wider range than is normally the case. The major contributions of the study have been in the field of algorithm formulation and development (Chapters 3 and 4), with smaller contributions in the hierarchical approach to the problem, in the modelling of the particular application, and in the project formulation, organisation, and implementation planning.

The following summarises specific original contributions to the state of the art as presented in this thesis:

1. Algorithm Formulation and Development

(a) The Dynostat Algorithm. (Chapter 4.2)
The Dynostat technique of imbedding a static optimisation method within a dynamic programming method has been a major contribution of the study. The technique achieves a marked reduction in computational requirements for dynamic optimisation of that class of system containing elements of differing dynamic responses. The method may be applied to both linear and non-linear systems, and allows for time varying system parameters and switching discontinuities.

(b) The On-line Dynamic Algorithm. (Chapter 4.2)
A technique for continuous input on-line updating of optimal dynamic trajectories has been evolved, based on the dynamic programming method. With this technique dynamic systems can be maintained in the most optimal configuration possible with respect to the system information available. A modified list programming technique has been developed and utilised in the computationally efficient hierarchy of sub-programs to implement the on-line concept.

(c) Sensitivity Analysis Algorithms. (Chapter 4.3)
A set of progressively more sophisticated algorithms to analyse the cost and constraint sensitivity of dynamic optimal trajectories has been developed. A Monte Carlo technique is utilised to randomly select disturbances to the system from appropriate distributions, and the system response under various conditions is assessed. The initial algorithms considered constraint sensitivity only, however the more sophisticated algorithms assessed both cost and constraint sensitivity.

(d) Analysis of System Dynamic Characteristics With Respect to Parameter Variation. (Chapter 3.2)

An algorithm has been developed to determine the effects of changing system parameters on the dynamic characteristics of the system. The algorithm gives a measure of the ability of the system to withstand peak demands on energy with different sets of parameter values, and is used in the long term iterative optimisation procedure. The method developed is a modified version of a sensitivity analysis algorithm.

Other material covered in the thesis, comprising modelling, management aspects, and proposed algorithms for which claims of academic originality cannot be made, are summarised below:

1. <u>Algorithm Formulation</u>

(a) An Iterative Procedure for Plant Optimisation in the Long Term. (Chapters 2.3 and 3.3)

An iterative procedure has been developed to determine the optimum system configuration over a long term planning horizon, as an aid to system planning and operation budgeting. The procedure permits the use of relatively simple static optimisation and sensitivity analysis techniques, and accounts for the effects of parameter variation on the dynamic characteristics of the system by incorporating the dynamic analysis algorithm (see (d) above). The complex objectives of the system, and its interaction with the outside world are accounted for by including the management group within the closed loop.

(b) Proposed Composite Dynamic Optimisation - Sensitivity Analysis Algorithm (Chapter 4.3)

A composite optimisation/sensitivity analysis technique for dynamic systems has been proposed. Monte Carlo or analytic techniques are used regressively to establish limits on the allowable system states, so as to ensure some given probability of goal satisfaction. The Dynostat (or alternative) optimising technique then selects the optimum trajectory within these limits. A simple extension to this technique provides a powerful regressive stochastic optimisation and sensitivity analysis algorithm. The trajectories obtained using this technique would: 1) be optimal with respect to probabilistic and deterministic disturbances (in an off-line sense, and: 2) have a probability of goal satisfaction above some given value.

(c) Proposed Heuristic Dynamic Optimisation Algorithm. (Chapter 4.2)

An heuristic algorithm for optimisation of multi-dimensional dynamic systems has been proposed. The technique uses learned system response to control actions to reduce the number of optimal route possibilities considered at each stage of the calculation. With multi-dimensional systems a considerable computational advantage can be gained, at the expense of certainty in the optimality of the resultant trajectories. Although developed from the dynamic programming technique, the method is more similar to the static feedforward techniques developed in Chapter 3.4.

2. Systematic Hierarchical Decomposition of the Overall Problem (Chapters 2.2 and 2.3)

One facet of the study has been the use of hierarchical concepts to decompose the overall problem into a number of related subproblems. This permits maximum utilisation of the specific features of the problem, and to a lesser extent of available technique. In addition, the specific problem under consideration may be readily co-ordinated with studies on other aspects of mill operation, or the scope of the specific problem may be simply expanded to include these other aspects. In a strict sense, these concepts are far from new - the approach here however, has been to apply hierarchical techniques as a design tool to coarsely structure the overall problem of mill operation, then to progressively focus on more and more details of the particular problem until the individual algorithms required could be identified and specified. This management aspect of the study has been reported in "A Systematic Approach to an Industrial Optimisation Problem" (See Section 6.4). The iterative procedure for plant optimisation in the long term in particular, is directly attributable to the use of this approach.

3. Modelling of the Tasman Mill System (Chapter 2.4)

The contributions within this field have been:

(a) The development of a mathematical model of the energy system at the Tasman Mill. The system model was expressed both in a "block diagram" form; and in a more general mathematical formulation.

(b) The use of an aggregation technique in the development of models of system structure. The aggregation method is an efficient modelling technique, and has the added advantage of giving a hierarchical structure of models. The model hierarchy can be readily expanded to any required level of detail so as to include any desired features of the system.

(c) The analysis of system disturbances, and the modelling of the resultant disturbance components.

4. Formulation and Planning of the Project (Chapters 1.2 and 5)

Throughout the course of the project, a specific effort has been made to ensure planned development of the study. This contribution encompasses three related aspects:

(a) selection and formulation of the project
(b) outline planning of the University studies
(c) development of a philosophy and plan for implementation of the study.

6.3 THE INTRODUCTION OF NEW TECHNIQUE TO THE FIRM

As discussed in Chapter 5, the plan for implementation of the results of this study is of necessity tentative, and dependent on many factors, outside the direct control of the student. One of the factors not taken into account in this planning was the current major mill expansion, then in its very early stages. This expansion has imposed a severe load on the engineering resources of the mill, with the inevitable result of postponing the planned implementation until suitable manpower is available. Some success can be noted in the introduction of the new expertise to the firm:

(a) An exploratory study on the application of the technique for analysis of system dynamic characteristics (see 1 (d) above) to the choice of the electrical maximum demand parameter, has been carried out.

(b) Interaction between the University group and the firm's control engineers has resulted in the application of a sophisticated feedforward automatic control system to a set of multi-effect evaporators. This is a pioneer application and will shortly be reported on.

(c) Following the proposals put forward for the formation of a Systems Engineering group at the firm, a Systems Engineer was appointed. The author has since joined the firm, and is also employed in this capacity. Currently the group is heavily committed with the design of control systems for the present mill expansion, however, it is anticipated that some effort will shortly be put toward the proposed implementation plan of Chapter 5.

6.4 DOCUMENTATION OF THE PROJECT

Documentation of the project other than this thesis falls into three groups; a) papers published in technical journals, b) internal reports to the firm, and c) seminars presented at the firm. These are as follows:

(a) Papers presented in technical journals:

1. "A Parallel Optimum Seeking Technique - Dynostat". J.A. Gibson, G.E. Coombes, IEEE Trans. on Systems Science and Cybernetics, Vol. SSC-6, No. 3, 1970.
2. "A Systematic Approach to an Industrial Optimisation Problem". G.E. Coombes. Presented at the 3rd Hawaii International Conference on Systems Sciences, 1970.

3. "A Sensitivity Analysis of Optimal Dynamic Trajectories". G.E. Coombes. Presented at the 3rd Hawaii International Conference on Systems Sciences, 1970.
4. "A Joint University-Industry Systems Study". J.A. Gibson, G.E. Coombes. Submitted to the Journal of Systems Engineering.
5. "A Computer-aided Approach to a System Optimisation Problem". J.A. Gibson, G.E. Coombes, T.W. Marks. Automation and Control, March 1971.

(b) Internal Reports to the Firm:

In addition to the normal six monthly progress reports, special reports have been presented as follows:

1. "Project - Power Optimisation at Tasman. Present Status, Future Plans as at May 1970".
2. "A Systematic Approach to an Industrial Optimisation Problem".
3. "A Monte Carlo Assessment of 'Probability of Production Loss versus Maximum Demand Value'".
4. Departmental Memo #76. "Energy Optimisation at Tasman - Problem Breakdown and Proposed Study Implementation Plan".

(c) Seminars Presented at the Firm:

Seminars have been given to engineers and management at the firm on three occasions:

1. Problem Breakdown using Hierarchical Techniques
2. The Dynostat Optimising Algorithm
3. A Monte Carlo Evaluation of M.D. Value.

In addition to the above papers, reports and seminars, a proposal for a Systems Engineering group at the firm was presented to management in 1970. On a subsequent visit, this proposal was discussed and a second document, "A Research Programme in the Department of Electrical Engineering, Unicant", was presented. A Systems Engineering group has since been formed.

6.5 FURTHER DEVELOPMENTS FROM THIS THESIS

Work is continuing in the general way outlined in Chapter 5 by other members of the group. Several areas of these studies aim at extending the developments of this thesis.

1. An improved mathematical formulation of the energy system at the Tasman mill has been achieved by Marks (1). This is a development of the form of model shown in Figures 2.17, 2.18.

2. Application of the Dynostat method using a hybrid computer has been a primary development. The dynamic section of the method lends itself to solution by the digital computer, while the repeated static optimisations can be readily solved using hill climbing techniques on the analogue computer. The use of sophisticated techniques derived from control theory in the design of the analogue algorithm, has allowed full utilisation of the parallel processing capability to achieve very high solution speeds with minimum loss in accuracy.

3. Further development in implementation of the Dynostat is under investigation. This involves the use of a serial digital computer interfaced with a parallel digital processer. The philosophy is as in the digital - analogue hybrid application with the dynamic problem being solved by the serial machine, and the static problem by the parallel processer. A prototype parallel digital optimiser has been constructed and successfully tested on a simple static optimisation problem.

4. Development of heuristic techniques for the solution of dynamic optimisation problems is under investigation. This algorithm should reduce the dimensionality problems of dynamic optimisation by a trade of " % confidence in solution" for "computation speed", using complementary deterministic

and probabilistic methods. It is expected that the techniques developed will be used to solve the dynamic section of the Dynostat computation, further increasing the power of this basic concept.

This research, and the other work outlined in Chapter 5 has two objectives:

(1) Final implementation of the best possible system for the optimisation of energy usage at the Tasman mill.

(2) Achieving an improvement in the state of the art of computer aided optimisation

Continuing research is yielding rapid improvements in computer hardware and software, decreasing costs and increasing speed and reliability. At the current rate of development, it will very soon be possible to extend the scope of computer-aided process optimisation and control beyond that envisaged in this thesis.

Such systems will ultimately provide integrated analysis, optimisation and control over the full range of activities within the company, from the process itself through to bookkeeping. Properly designed and operated systems of this nature will yield a primary return by releasing labour for alternative tasks, but will also give secondary returns by virtue of closer control, better efficiency, and the integrated nature of the system.

The human decision making facility with its incredible flexibility cannot be dispensed with in the foreseeable future, but it can be relieved of much of the tedium and many of the menial tasks now required of it. In this way the introduction of comprehensive computer control systems will remove one of the dehumanising side effects of capital intensive industry - reversing a trend begun with the first production lines.

The use of these comprehensive systems will not be restricted to industry, but will spread into every field of human activity from commerce, to the regulation and control of society. The nett effect on our society will be marked - whether for good or otherwise will depend on realistic and far-sighted planning, which with the rapid development of a field still in its infancy, is required now.

REFERENCES CHAPTER 6

1. T.W. Marks: "High Speed Computer - Aided Optimization in Engineering"
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